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Demand Forecasting: DLA'S Aviation Supply Chain High Value Products

9 April, 2015

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14. ABSTRACT
This study set out to provide the Defense Logistics Agency (DLA) a set of demand forecasting and risk modeling tools and techniques to help both achieve target service levels and quantify the risk of stock-outs in the DLA aviation supply chain. This vision culminated in a simple process that all together takes between 1 to 2 hours to understand a product???s demand volume, pattern, probability distributions as well as quantifying the risk of stock-outs. Perhaps an easier way to think about this study is that it became a discussion about buying the right stuff at the right quantity and at the right time. The result of this study is the recommendation of three actions to (1) identify the few stock items that have the greatest impact on the organization???s annual budget (2) use the forecasting and risk modeling technique described herein to calculate adequate inventory for the target service level(s) and (3) execute a lean six sigma project to reduce drivers for the organization???s risk exposure. A higher risk exposure influences the decision to carry more safety stock; thus creating a vicious cycle of increased material costs.

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DEMAND FORECASTING: DLA'S AVIATION SUPPLY CHAIN HIGH VALUE PRODUCTS

ABSTRACT

This study set out to provide the Defense Logistics Agency (DLA) a set of demand forecasting and risk modeling tools and techniques to help both achieve target service levels and quantify the risk of stock-outs in the DLA aviation supply chain. This vision culminated in a simple process that all together takes between 1 to 2 hours to understand a product's demand volume, pattern, probability distributions as well as quantifying the risk of stock-outs. Perhaps an easier way to think about this study is that it became a discussion about buying the right stuff at the right quantity and at the right time. The result of this study is the recommendation of three actions to (1) identify the few stock items that have the greatest impact on the organization's annual budget (2) use the forecasting and risk modeling technique described herein to calculate adequate inventory for the target service level(s) and (3) execute a lean six sigma project to reduce drivers for the organization's risk exposure. A higher risk exposure influences the decision to carry more safety stock; thus creating a vicious cycle of increased material costs.

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LIST OF ACRONYMS AND ABBREVIATIONS

AIC	Akaike Information Criterion
ALT	Admin Lead Time
BSM	Business Systems Modernization
CAIC	Corrected Akaike Information Criterion
CVAR	Conditional Value at Risk
DLA	Defense Logistics Agency
DORRA	DLA Office of Operations Research and Resource Analysis
LTD	Lead-Time Demand
NIIN	National Item Identification Number
PLT	Procurement Lead Time
ROP	Reorder Point
SS	Safety Stock
SL	Service Level

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EXECUTIVE SUMMARY

The purpose of this research is to provide DLA a set of demand forecasting and risk modeling tools and techniques to help both achieve a 95% fill rate and quantify the risk of stock-outs in the aviation supply chain.

A. WHY IS THIS RESEARCH IMPORTANT?

This research can become an input that adds value to DLA's planning cycle, including appropriate demand forecasting techniques working in concert with improved inventory policy and other internal processes that enable the organization to both improve use of cash flows for buying the right stuff and reduce the inventory replenishment cycle (lead time) to reduce material carrying costs:

- Re-setting inventory policy
- Reducing internal administrative lead-time and
- Negotiating with suppliers for shorter replenishment cycles

B. METHODOLOGY

This research presents the following process for (1) understanding demand volume, patterns and probability distributions for (2) producing useful models for lead-time demand forecasts (3) in order to formulate effective inventory policy:

- Identifying the few stock items that have the greatest impact on the annual budget
- Analyzing product demand history and providing visual representation to accelerate understanding of demand volume, patterns and probability distribution
- Forecasting technique using probability distribution
- Resetting inventory Policy: Reorder Point (R) and Safety Stock (SS) levels
- Measuring stock-out risk using Monte Carlo simulations (What is the expected shortage? How bad can things get?)

C. INVENTORY CLASSIFICATION IDENTIFIES THE FEW STOCK ITEMS WITH GREATEST IMPACT ON ANNUAL REVENUE OR BUDGET

Because labor hours is a scarce resource, an inventory manager should allocate more time to identifying and closely managing those inventory items that have the greatest impact on the DLA cash flows and annual budget. The ABC classification method is a way to identify material according to its impact on the annual revenue or budget (Chapter 3). The top 10 percent of total NIINs that have the most impact are grouped in "class-A," "class-B" items are the next 40 percent of the total stock items and "class-C" are the remaining 50 percent of total stock items. ***The benefit of this classification method is that it separates the few inventory items that have the greatest impact on annual revenue (or annual budget).*** Therefore, class-A stock is the focus of this research project. As shown in Figure 1, class-A stock, 10% of all NIINs, accounts for almost 80% of total revenue in FY2013.

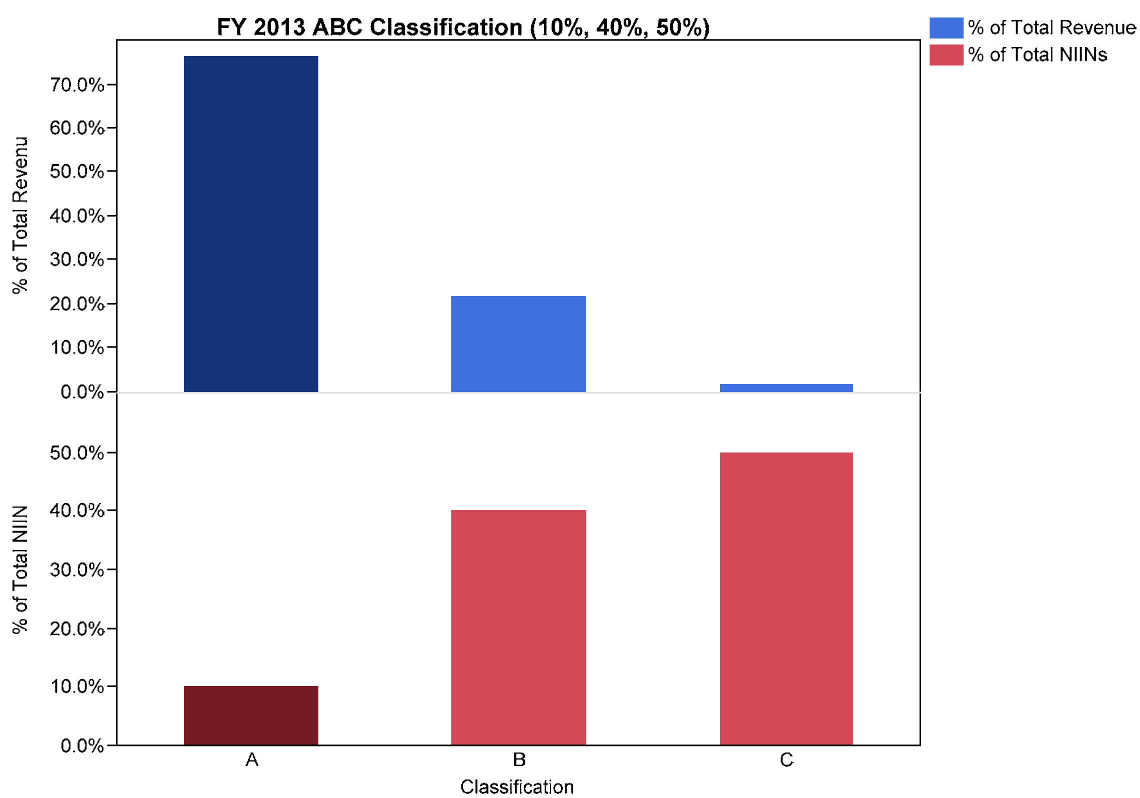

Figure 1. FY2013 ABC Classification

The ABC classification method can be modified to fit the DLA leadership requirements. For example, DLA stock is assigned criticality codes. As an alternative, the steps above can be modified to list stock in descending order according to criticality code. This would also help the inventory manager in identifying inventory that requires more time allocated to managing inventory levels.

D. STATISTICAL ANALYSIS, FORECASTING TECHNIQUES AND RISK MEASURE USED IN THIS RESEARCH

DLA provided a great amount of actual product demand data for this research, totaling over 5 million requisition records for the period of October 2009 to March 2014. We used JMP PRO 10 statistical analysis tool to examine two variables, date and demand quantity, to produce an abundance of statistical information, summarize and organize information in tables and graphs to accelerate understanding of stock revenue, demand pattern, demand probability distribution and replenishment lead time by stock item (NIIN).

We first looked to gain an understanding of the total value of revenue generated by DLA aviation supply chain from FY2010 to FY2013. This is shown in Table 1.

	Revenue	qty_req
FY	**Sum**	**Sum**
2010	$2,692,055,593	24,139,182
2011	$3,145,200,422	23,675,167
2012	$3,323,996,371	21,721,754
2013	$2,600,361,361	17,904,558

Table 1. DLA Supply Chain Revenue FY2010-FY2013

For the purpose of this Executive Summary, we will take a snapshot of the demand of just one of the NIINs that counts towards largest share of FY2013 revenue, the Vertical Stabilizer (NIIN 01–525–1263). The demand pattern for this item is depicted in Figure 2.

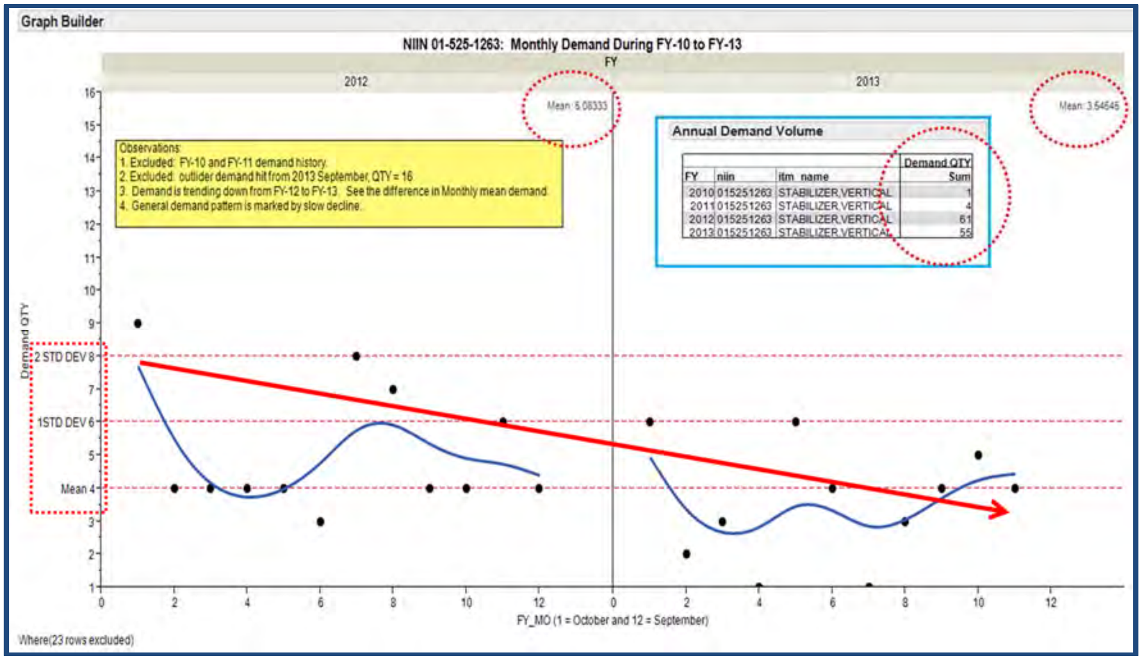

Figure 2. Monthly Demand Vertical Stabilizer FY2010 – FY2013

After looking at the demand pattern, we then used JMP Pro 10 to find the probability distribution that best fits historical the demand pattern. The Vertical Stabilizer probability distribution tests are depicted in Figures 3 and 4.

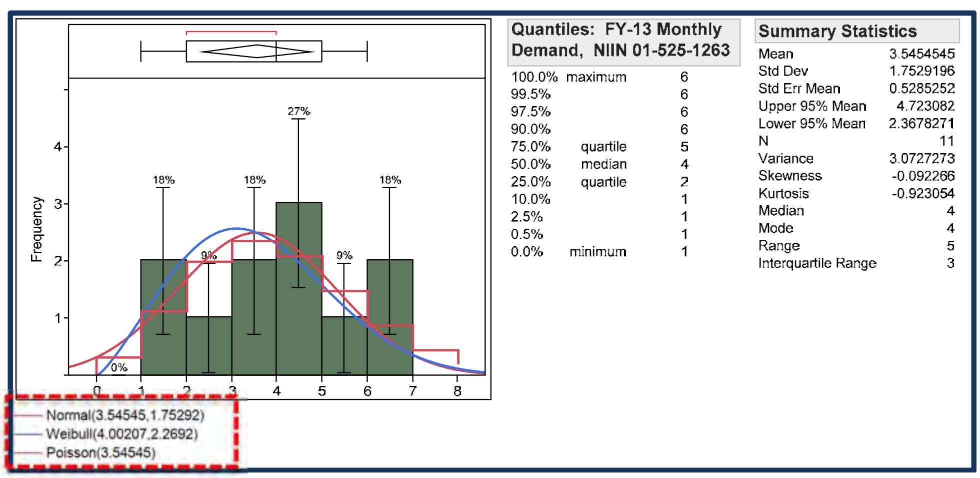

Figure 3. Vertical Stabilizer Probability Distributions

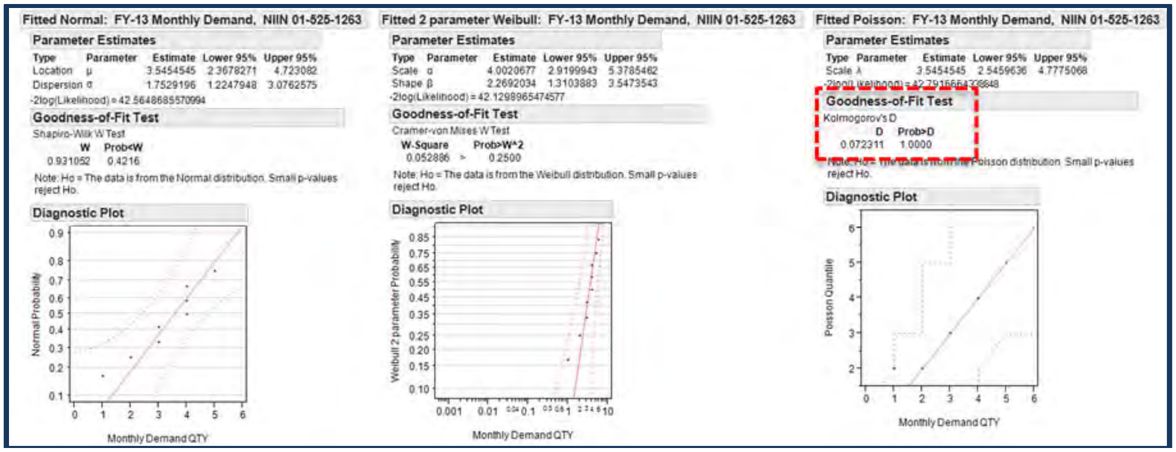

Figure 4. Probability Distribution Fit Test

After determining the probability distribution and associated parameters, we determined the material replenishment lead time. Table 2 shows the trend for admin (alt) and procurement lead time (plt) for the Vertical Stabilizer. In FY2014, the total lead time is 960 days, or about 32 months.

Tabulate: NIIN 01-525-1263

								qty_req	Revenue	alt				plt		
FY	Quarter	FY_MO	FY_MO Series	Calendar Month	niin	itm_name	std_u_price	Sum	Sum	30	84	90	120	540	840	999
2010	1	2010_3	3	12	015251263	STABILIZER,VERTICAL	$644,655.54	1	$644,655.54	0	0	1	0	0	0	1
2011	2	2011_5	5	2	015251263	STABILIZER,VERTICAL	$833,496.88	1	$833,496.88	1	0	0	0	1	0	0
		2011_6	6	3	015251263	STABILIZER,VERTICAL	$833,496.88	2	$1,666,993.76	2	0	0	0	2	0	0
	4	2011_11	11	8	015251263	STABILIZER,VERTICAL	$814,849.15	1	$814,849.15	1	0	0	0	0	1	0
2012	1	2012_1	1	10	015251263	STABILIZER,VERTICAL	$814,849.15	9	$7,333,642.35	5	0	0	0	0	5	0
		2012_2	2	11	015251263	STABILIZER,VERTICAL	$814,849.15	4	$3,259,396.60	2	0	0	0	0	2	0
		2012_3	3	12	015251263	STABILIZER,VERTICAL	$814,849.15	4	$3,259,396.60	3	0	0	0	0	3	0
	2	2012_4	4	1	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	1	0	0	0	0	1	0
		2012_5	5	2	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	2	0	0	0	0	2	0
		2012_6	6	3	015251263	STABILIZER,VERTICAL	$786,329.43	3	$2,358,988.29	2	0	0	0	0	2	0
	3	2012_7	7	4	015251263	STABILIZER,VERTICAL	$786,329.43	8	$6,290,635.44	5	0	0	0	0	5	0
		2012_8	8	5	015251263	STABILIZER,VERTICAL	$786,329.43	7	$5,504,306.01	3	0	0	0	0	3	0
		2012_9	9	6	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	2	0	0	0	0	2	0
	4	2012_10	10	7	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	0	0	3	0	3	0
		2012_11	11	8	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	0	0	3	0	3	0
		2012_12	12	9	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	0	0	3	0	3	0
2013	1	2013_1	1	10	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	3	0	0	0	3	0
		2013_2	2	11	015251263	STABILIZER,VERTICAL	$749,864.65	2	$1,499,729.30	0	1	0	0	0	1	0
		2013_3	3	12	015251263	STABILIZER,VERTICAL	$749,864.65	3	$2,249,593.95	0	2	0	0	0	2	0
	2	2013_4	4	1	015251263	STABILIZER,VERTICAL	$749,864.65	1	$749,864.65	0	1	0	0	0	1	0
		2013_5	5	2	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	3	0	0	0	3	0
		2013_6	6	3	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	2	0	0	0	2	0
	3	2013_7	7	4	015251263	STABILIZER,VERTICAL	$749,864.65	1	$749,864.65	0	1	0	0	0	1	0
		2013_8	8	5	015251263	STABILIZER,VERTICAL	$749,864.65	3	$2,249,593.95	0	2	0	0	0	2	0
		2013_9	9	6	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	2	0	0	0	2	0
	4	2013_10	10	7	015251263	STABILIZER,VERTICAL	$782,639.44	5	$3,913,197.20	0	2	0	0	0	2	0
		2013_11	11	8	015251263	STABILIZER,VERTICAL	$782,639.44	4	$3,130,557.76	0	2	0	0	0	2	0
		2013_12	12	9	015251263	STABILIZER,VERTICAL	$782,639.44	16	$12,522,231.04	0	7	0	0	0	7	0
2014	1	2014_3	3	12	015251263	STABILIZER,VERTICAL	$782,639.44	9	$7,043,754.96	0	3	0	0	0	3	0
	2	2014_5	5	2	015251263	STABILIZER,VERTICAL	$782,639.44	1	$782,639.44	0	0	0	1	0	1	0

Table 2. Vertical Stabilizer Procurement and Admin Lead Time

Next, we created demand forecast simulation models. To do this, Crystal Ball software produced Monte Carlo simulations using the total lead time and selected probability distribution to display results of a forecast as well as a measure of stock out risk. Figure 5 below shows the Monte Carlo simulation for lead-time demand during the 32 month replenishment cycle for the Vertical Stabilizer (NIIN 01–525–1263). The forecast for average demand is a total of 53 units and the required stock quantity for a 95 percent service level is 65 units. While the forecasted demand for this NIIN is low, the per unit value is more than $782 thousand and during FY2013 accounted for the highest annual revenue in the DLA aviation supply chain.

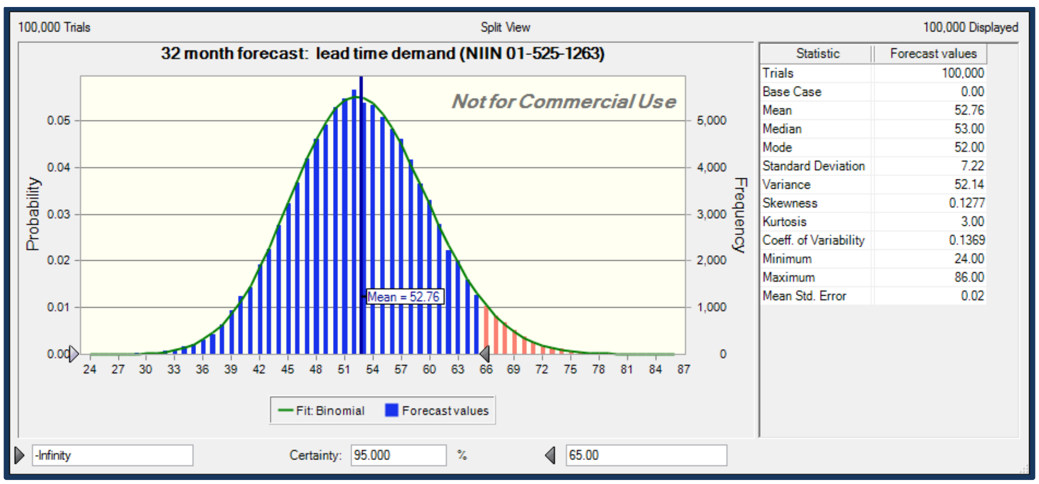

Figure 5. Lead Time Demand Monte Carlo Forecast Simulation

Figure 6 shows the conditional value at risk, which is the expected shortage in the event of a stock out, computed as follow:

Expected stock out quantity less 95 percent service level quantity =

69 – 65 = 4 units short

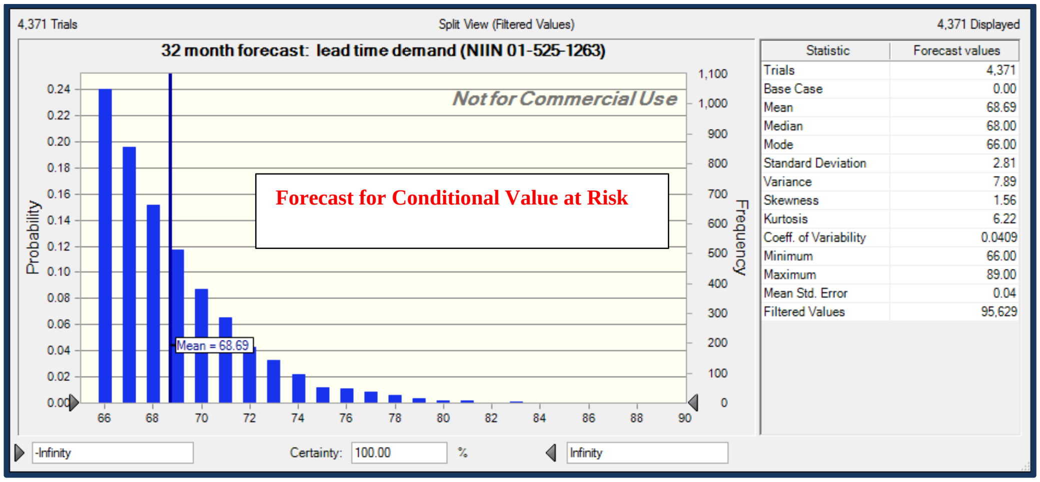

Figure 6. Monte Carlo Forecast Simulation of Stock-out Risk

E. LEAD-TIME DEMAND (LTD) FORECAST: THE RIGHT INPUT FOR INVENTORY MANAGEMENT POLICY

While it can be helpful to visualize product demand in blocks of days, weeks, months or years, representing demand in said time segments does not necessarily provide the most useful information for reordering stock in accordance with an inventory policy. A much improved way to visualize product demand is by service level and probability distribution during the replenishment cycle (*lead-time demand).* In other words, as shown in Figure 5, a Monte Carlo forecast simulation provides lead-time demand forecast for the target service level. The target service level quantity tells a forecaster (or inventory manager) the inventory quantity needed and when to reorder between stock replenishments cycles to meet a target service level.

Figure 7 shows a gallery of probability distributions and in our research, the most common were the Poisson, Normal and Lognormal distributions.

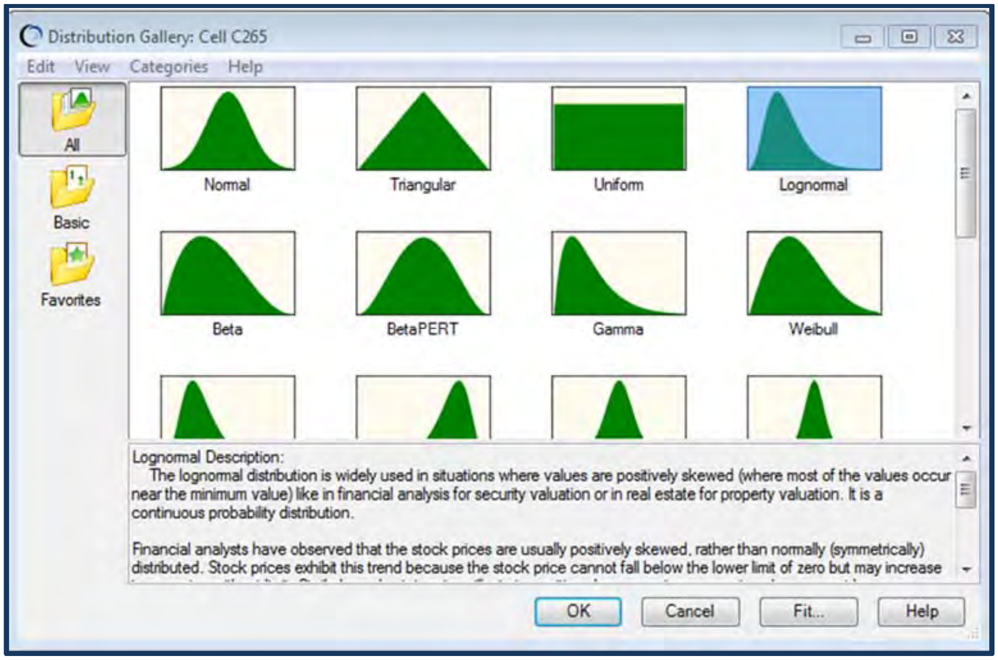

Figure 7. Probability Distribution Gallery

F. INVENTORY POLICY FORMULATION

An effective inventory management model minimizes the total cost of attaining the target service level. In our analysis and appendices we produce demand forecasts based on probability distribution of actual demand. Use of the right demand distribution in the forecast model is key to reducing material cost and material holding cost because identifying the right demand distribution produces a forecast model with adequate safety stock quantity for a target service level. In other words, excess stock is minimized because for each NIIN, target service level quantity is different, unique, according to the probability distribution used in the lead-time demand forecast model. Figure 8 illustrates this concept.

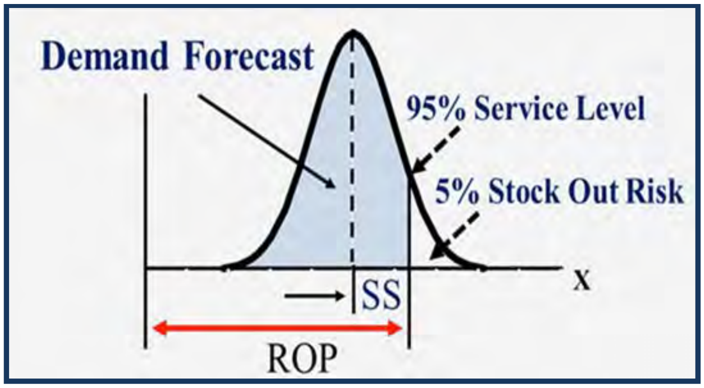

Figure 8. ROP and Safety Stock

Therefore, matching the right demand distribution with each NIIN's demand forecast is essential to reducing inventory cost with the added benefit of reasonable confidence that the target service level will be achieved during the lead time (or the risk exposure period). Simply put, the Monte Carlo simulations provide critical information needed to formulate an effective inventory policy.

Recall that safety stock is insurance incorporated into a target service level (or fill rate) to guard against the risk of stock outs during replenishment cycles. Higher demand variability results in more required safety stock. Longer lead time combined with demand variability compounds the need for more safety stock to guard against the risk of stock outs during the replenishment cycle, which explains increasing material costs and holding costs. With that understanding and continuing with the example of the Vertical Stabilizer, we compute the material costs and holding costs as follows:

- Holding cost of forecast inventory:

  Total Holding Cost = (Unit Holding Cost) (Safety Stock + Cycle Stock/$\mathbf{2}$)

  Current = (18% * $782,639.44) ($\mathbf{168}-\mathbf{53}$ + ($\mathbf{53}/\mathbf{2}$) = $19,933,836.54

  Proposed = (18% * $782,639.44) ($\mathbf{65}-\mathbf{53}$ + ($\mathbf{53}/\mathbf{2}$) = $5,423,691.32

  <u>Potential Holding Cost Decrease = $14,510,135</u>

(Note: sales price used in lieu of cost. Also, 53 units is this project's forecast quantity for lead time demand.)

- Forecast material cost, or if not sold, dead weight on the shelf (selling price used because procurement cost is unknown):

$$\text{Material Cost} = \boldsymbol{cost\ x\ Quantity}$$

Current = $\boldsymbol{782{,}639.44\ x\ 1}$68 = \$131,483,425.90

Forecast = $\boldsymbol{782,.44\ x\ 65}$= \$50,871,563.60

<u>Potential Material Cost Decrease = $80,611,862</u>

- Demand forecast simulations were completed for a total of fifty NIINs belonging to the FY2013 Class A stock category. The potential material cost reductions were:

<u>Potential Holding Cost Decrease = ~$60 million</u>

<u>Potential Material Cost Decrease = ~$300 million</u>

G. SUMMARY

In conclusion, we recommend three actions. First, use the ABC Classification method to identify the few stock items that have the greatest impact on the organization's annual budget. Inventory levels of the Class A NIINs should be monitored closely. Second, use the forecasting and risk modeling technique described herein to calculate adequate inventory for the target service level. Third, execute a lean six sigma project to reduce lead time (both admin and procurement lead time). The longer the lead time, the more money it costs the organization to pay for operations in the form of material costs and inventory holding cost. This is because lead time and demand variability combine in the form of risk exposure. A higher risk exposure influences the decision to carry more safety stock. While DLA does not influence demand variability, the organization should use its purchasing power to influence decreased supplier lead time. On the other hand, decreased lead time lowers the risk exposure and this knowledge should incentivize inventory managers to decrease inventory levels; thus, resulting in decreased material costs.

ACKNOWLEDGMENTS

This MBA professional report represents not only our work at the keyboard but also the contributions of many.

Foremost, we would like to recognize where the most basic source of life energy resides, our families. We would like to thank our spouses, Erika Guerra and Angelica Guerrero, as well as our children for their tremendous love, support and encouragement in our writing of this MBA Project. We cannot express enough appreciation and thanks for their understanding as we dedicated ourselves to this research and they all sacrificed much during the past eighteen months. We share the credit of our work with you.

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I. INTRODUCTION

The Defense Logistics Agency (DLA) is supported by about 26,000 civilian and military employees who manage eight supply chains, 25 distribution centers worldwide, and almost 6 million differentiated stock items. The Agency claims to processes an average of 98,475 requisitions and 9,000 contract actions daily. If DLA were a commercial company, the dollar value of products and services it provides would place it in the top 15th percentile of Fortune 500 companies (DLA, 2014). In 2013, DLA announced plans to save $13.1 billion in operating and material costs over the next six years, in keeping with the Agency Director's austerity initiative (Boyer, 2013). Since announcing its cost-cutting initiative DLA has:

- Decreased direct material costs using reverse auction opportunities to save more than $1.6 billion over the past year (Harnitchek, 2014, p. 4)
- Achieved savings of $6 million to $7 million per month on pharmaceutical contracts (Harnitchek, 2014, p. 8)
- Reduced its response time for the 5th Fleet by 81 percent from 40 days to eight days (Harnitchek, 2014, p. 5)
- Reduced inventory by $2 billion since 2012, including a decrease in contingency stock from $2 billion to about $500 million (Harnitchek, 2014, p. 8)

Central to achieving DLA's objective of continued slashing operating and materiel costs is the implementation of new methods of inventory control focused on DLA's ability to generate and act upon accurate demand forecasts. The purpose of this research is to provide the DLA with a set of demand forecasting tools as part of the continuous planning process to decrease inventory costs, or in other words, to ensure that the organization can purchase "the right stuff, at the right time, and in the right quantity" (Stratman, 2011, p. 2). However, this research paper argues that demand forecasting is only one part of the equation needed to continue slashing DLA material costs. This study provides a set of statistical analysis, forecasting, and risk modeling techniques to help achieve target service levels set by DLA, and to quantify and dollarize stock out risk of items in the aviation supply chain.

DLA is responsible for nearly six million differentiated stock items moving through eight supply chains. This research can become an input that adds value to DLA's planning cycle, including appropriate demand forecasting techniques and considerations for an inventory policy that can reduce material carrying costs (identifying the few stock items that have the greatest impact on the annual budget and re-setting inventory policy based on improved forecasts) plus a discussion on reducing the risk exposure period or cycle time (lead time), which is an irresistible influence on the decision to carry higher inventory levels and is a driver for higher material costs.

Cost reduction forms a key component in DLA's strategy for significantly improving support to the warfighter while dramatically slashing the cost of operations and the cost of material. In the Director's Guidance (Harnitchek, 2014), DLA Director Vice Admiral Mark Harnitchek called this strategy "The Five Big Ideas," with three out of five ideas focused on cost reduction:

1. DLA should seek to "delight its customers" by improving customer service. The Agency proposes to do this by measuring its performance using customer standards and by increasing and reinforcing customer/supplier collaboration to achieve superior levels of inventory management.

2. DLA should decrease direct material costs with the goal attaining overall savings of $13 billion through 2019. The Agency plans to achieve these savings using a combination of reverse auctions, significant industry partnerships, performance-based logistics, and prime vendor contracts.

3. DLA proposes to reduce operating costs by a combination of eliminating, consolidating, and co-locating infrastructure; by optimizing the Agency's global distribution network; by incorporating an ongoing series of process improvements; and by "going green" at DLA operating locations.

4. DLA proposes to right-size its inventory by better managing both War Reserves and operational inventory. The Agency plans to review and adjust strategic requirements, improve its forecasting accuracy and planning, leverage its supply chains, and reduce its logistical footprint.

5. DLA intends to demonstrate its commitment to transparency and accountability by aggressively pursuing its goal of audit readiness. The Agency plans to focus on achieving a culture of judiciousness, meeting its assertion dates, and finding and pursuing improvement opportunities that produce accurate data that is in compliance with the rules.

DLA wants to stay a step ahead of customer requirements by anticipating demands before they escalate to urgent status. In keeping with this philosophy, DLA forecasts demand so that supplies it procures may be pre-positioned when and where customer needs require. In 2002, DLA modernized its approach to demand planning by rolling out its Business Systems Modernization (BSM) acquisition program. This BSM investment transitioned from a forecasting model based primarily on historical data to a model using customer-based demand forecasting units and data exchange. DLA claims this change resulted in improved forecasting accuracy throughout DLA. However, with the anticipated scaling down of military operations, DLA anticipates the need for fewer parts. Consequently, inventory planners must take a proactive approach to anticipating warfighter needs in this dynamic market by adopting new and improved forecasting techniques. This is due to the reality that excess inventory drives up DLA holding costs which are passed on to the customer in the form of higher selling price.

DLA is preparing to enter a new era of shrinking Department of Defense budgets and a digital age which is pushing increased business practice agility and dynamism. To respond to these transformative conditions, the Agency will seek to "optimize [the] ability to provide flexible logistics response through the expanded use of strategic supplier arrangements, performance-based agreements, and tailored logistics support" through both "continued innovation" and applied "logistics best practices" (Defense Logistics Agency, n.d., p. 10). In order to optimize inventory in this new era of austerity, the proposed tools introduce more effective product demand statistical analysis methods that will lead to more accurate forecasts, thereby reducing materiel cost while helping to attain target service level(s).

The process to be discussed in greater detail in Chapters II and III is helpful in uncovering inventory item relationships, understanding demand volume and patterns, probability distribution, producing lead-time demand forecasts, leveraging information for inventory management, and accounting for risk of stock-outs. Chapter IV describes analysis and summary forecast results. We used appendices to immerse the reader in the product demand history analysis with visual representations to accelerate understanding of demand patterns and probability distributions. Also, each of the appendices present a

number of Monte Carlo simulation forecasting models and risk analysis of stock-outs. Critical inventory policy variables are examined: Reorder Point (R) and Safety Stock (SS) levels.

In terms of statistical tools, this study uses JMP Pro 10 and Oracle Crystal Ball in order to visualize demand patterns and generate forecasts. JMP Pro is used by analysts, engineers, statisticians, data scientists, modelers, and data miners in various industries for predictive modeling (SAS, n.d.). Oracle Crystal Ball is used by strategic planners, financial analysts, scientists, entrepreneurs, CPAs, marketing managers, venture capitalists, consultants, Six Sigma professionals and others who use spreadsheets for purposes of forecasting uncertain results (Oracle, 2014). The DLA currently employs multiple methods to account for demand variance, produce forecasts, and manage inventory, including Fourier, multiple linear regression, Holt-Winters, Lewandowski, and Croston's method (Nobel & van der Heeden, 2000). This study attempts to ascertain in a more effective way to forecast demand in a dynamic business environment for improved inventory control. The next chapter is dedicated to a review of current literature that deals with statistical analysis, forecasting, inventory management, and risk assessment.

II. LITERATURE REVIEW OF STATISTICAL ANALYSIS, FORECASTING, AND RISK MEASUREMENT

This chapter discusses a range of concepts from organizing information to statistical analysis and forecasting. Sections of discussions include:

A. Service level, fill rate, and conditional value at risk
B. ABC inventory classification
C. Statistical-analysis techniques
D. Description and use of goodness of fit for probability distributions
E. Forecasting techniques
F. Inventory-management policy
G. Measuring risk of stocking out

A. SERVICE LEVEL, FILL RATE, AND CONDITIONAL VALUE AT RISK

The material presented in this research project relies heavily on the use of two inventory management concepts, along with the measurement of risks for inventory stock out (out-of-stock prior to delivery of replenishment):

- **Service Level** (SL) is the evaluation of the likelihood for stock out during a number of stock replenishment cycles. SL is an inventory effectiveness policy. However, SL does not offer an assessment of the detrimental effects of allowing the inventory to run out (Doerr, 2014). In other words, SL can gauge the odds of being left without stock, but it is not able to explain the quantity of a stock-out. SL is the percentage of ordering sequences without stock-out (Ferrer, 2014):

$$Service\ Level = 1 - \frac{Number\ of\ cycles\ with\ shortage}{Total\ number\ of\ cycles}$$

- **Fill Rate** is the proportion of demand met from supplies already available. It is a client service metric. Fill rate is almost constantly higher than SL. However, fill rate does not account for the risk involved if stock becomes fully depleted (Doerr, 2014). Again, this measurement can estimate the likelihood of having provisions on hand, but cannot assess the negative impact of such a situation. Fill rate is the measure of orders satisfied from existing inventory (Ferrer, 2014):

$$Fill\ Rate = 1 - \frac{Number\ of unfulfilled\ orders}{Total\ number\ of\ orders}$$

- **Conditional Value at Risk** (CVAR) is the assessment of risk involved with the anticipated stock shortage, given that a logistics outcome (e.g., service level = 95%) *will not* be attained. Thus, the following questions can be answered by conducting a Monte Carlo simulation (Doerr, 2014):
  - "What is the expected cost (or quantity) of an inventory stock out? (For example, the average)"
  - "What is the high/low range of possible stock out?"

Note: When a forecaster provides the CVAR to an inventory manager, he creates a feedback loop that enables the inventory manager to make informed decisions about adjusting the inventory reorder point, either to lower inventory costs or to improve performance toward meeting a desired service level.

B. ABC INVENTORY CLASSIFICATION

The ABC classification method, which identifies the few stock items that have the greatest impact on the annual budget, categorizes material according to its level of impact on the annual budget (Ferrer, 2014, p. 212). The ABC Classification process is straightforward and can be accomplished using the data from the previous fiscal year. Because labor hours are a limited resource, an inventory manager should allocate additional time for identifying and carefully managing those inventory items that have the greatest impact on the DLA's cash flows and annual budget.

The ABC identification model is conducted through a series of steps. First, a spreadsheet including all stock items is created. Second, a column reflecting the Total Revenue (or Total Cost) is generated, and subsequently populated by multiplying Annual Demand × Unit Price. Third, this stock list should be arranged in descending order, listing first the stock items with the highest total annual revenue or total annual cost. Fourth, a "% of Total" column is added to the spreadsheet. Fifth, a "Cumulative % of Total" column is added (Ferrer, 2014). By organizing data in this manner, items that have the greatest budgetary impact can now be easily identified.

Upon completion of the previously described steps, the inventory stock list provides the inventory manager with the valuable ABC categorization information. According to the ABC classification method, Class A" stock items are the top 10% of the total inventory. Class B objects are the next 40% of the total stock items. Class C objects are the remaining 50% of the total inventory. The benefit of this classification method is that it separates the few inventory items that have the greatest impact on Annual Revenue or Annual Budget (Ferrer, 2014)**.** Chapter IV provides summary analysis of FY2013 Class A stock. Exhibit A provides a list of all FY2013 Class A stock.

The ABC classification system can be modified to fit DLA leadership requirements. For example, DLA inventory is assigned criticality codes. As an alternative, the steps above can be altered to list stock in descending order according to criticality code. This would also help the inventory manager to recognize the inventory that requires more time dedicated toward monitoring supply levels.

C. STATISTICAL ANALYSIS TECHNIQUES USED IN THIS RESEARCH

Data analysis can be done using simple statistical techniques using JMP software. For the purpose of our research, we used tables listing annual demand volumes, time series analysis using X by Y graphs, histograms and probability distribution tests.

- **Oracle Crystal Ball: Probability-Fit Distribution Test**

The DLA provided an abundance of concrete product demand data for this research for the period of October 2010 to March 2014.

Crystal Ball software was initially used in this research for fitting probability distribution curves with the demand data. A screenshot of the Crystal Ball function allowing the user to either choose a demand distribution from the menu, or select the "Fit" function in order to input a range of values for Crystal Ball to analyze before recommending a probability fit distribution for running a forecast model is displayed in Figure 1.

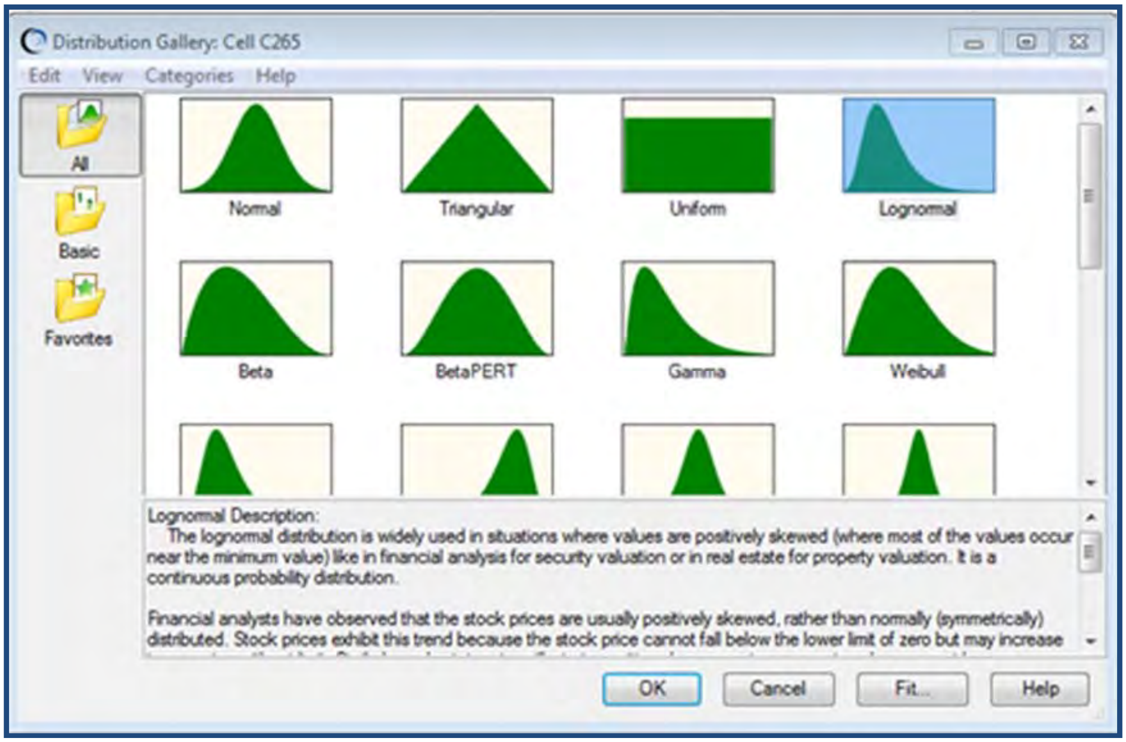

Figure 1. Description of Probability Distributions: Crystal Ball (User Guide, 2014, p. 50)

However, JMP software was a more powerful and easy to use tool for conducting statistical analysis and preparing visual representations of such analysis. For example, Figure 2, generated using JMP, shows a wealth of statistical information which can be applied to further calculations, forecasts, and risk assessment. Therefore, JMP was the software we used primarily for statistical analysis.

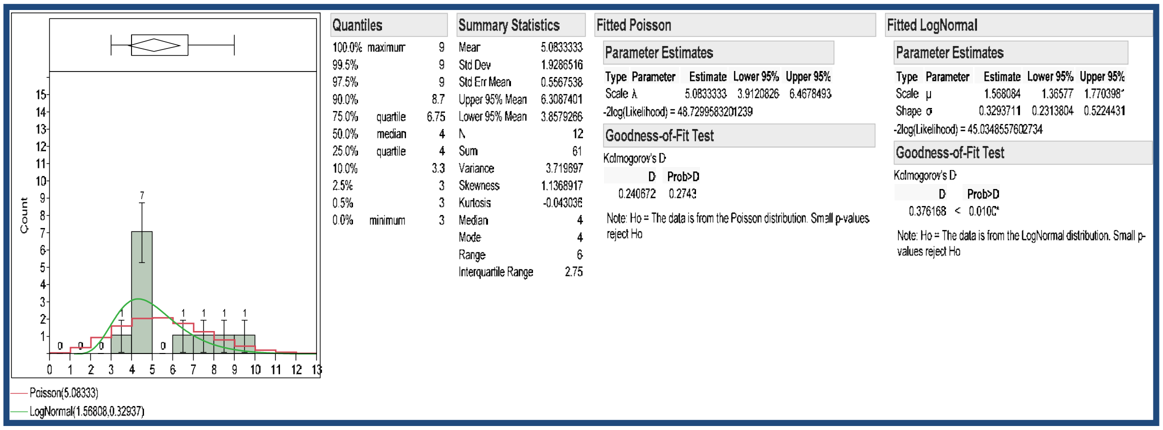

Figure 2. Example of Univariate Analysis Product (SAS, 2012, p. 32)

- **JMP X by Y Analysis of Demand**

This computation examines how the distribution of a continuous numerical variable Y (such as demand quantity) differs across sets defined by an unconditional X such as a time series (Proust, 2012). This method provides clear visual representation of patterns (or randomness) over an amount of time. An example is shown in Figure 3.

- **JMP: Bivariate Pattern Analysis**

The Bivariate graph platform is the continuous by continuous character of the Fit Y by X platform. Similar to the graph above, the Figures 4 and 5 show scatterplots that can be used to visualize demand trend (SAS, 2012, p. 91).

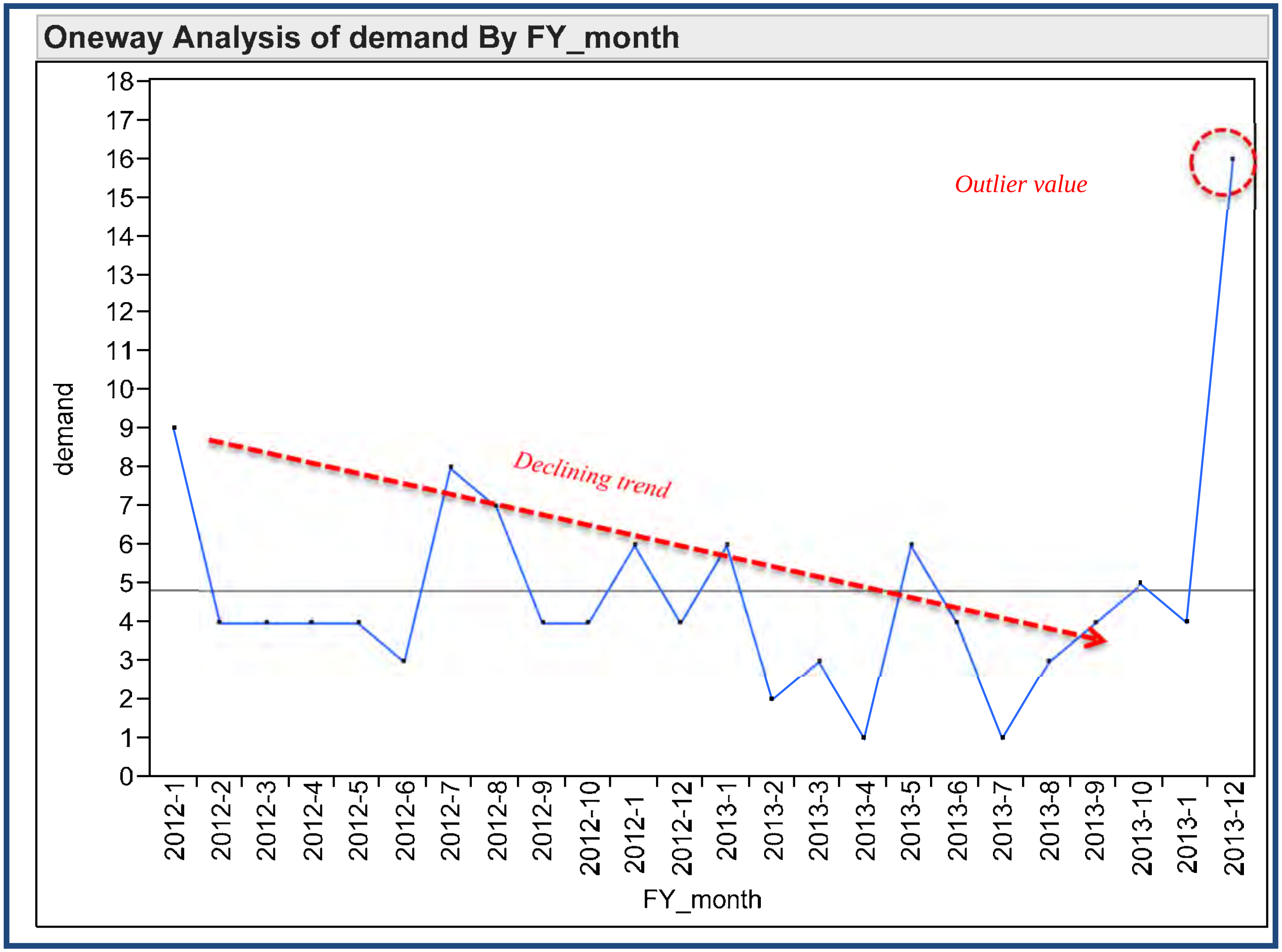

Figure 3. One Way Analysis of Demand (SAS, 2012, p. 87)

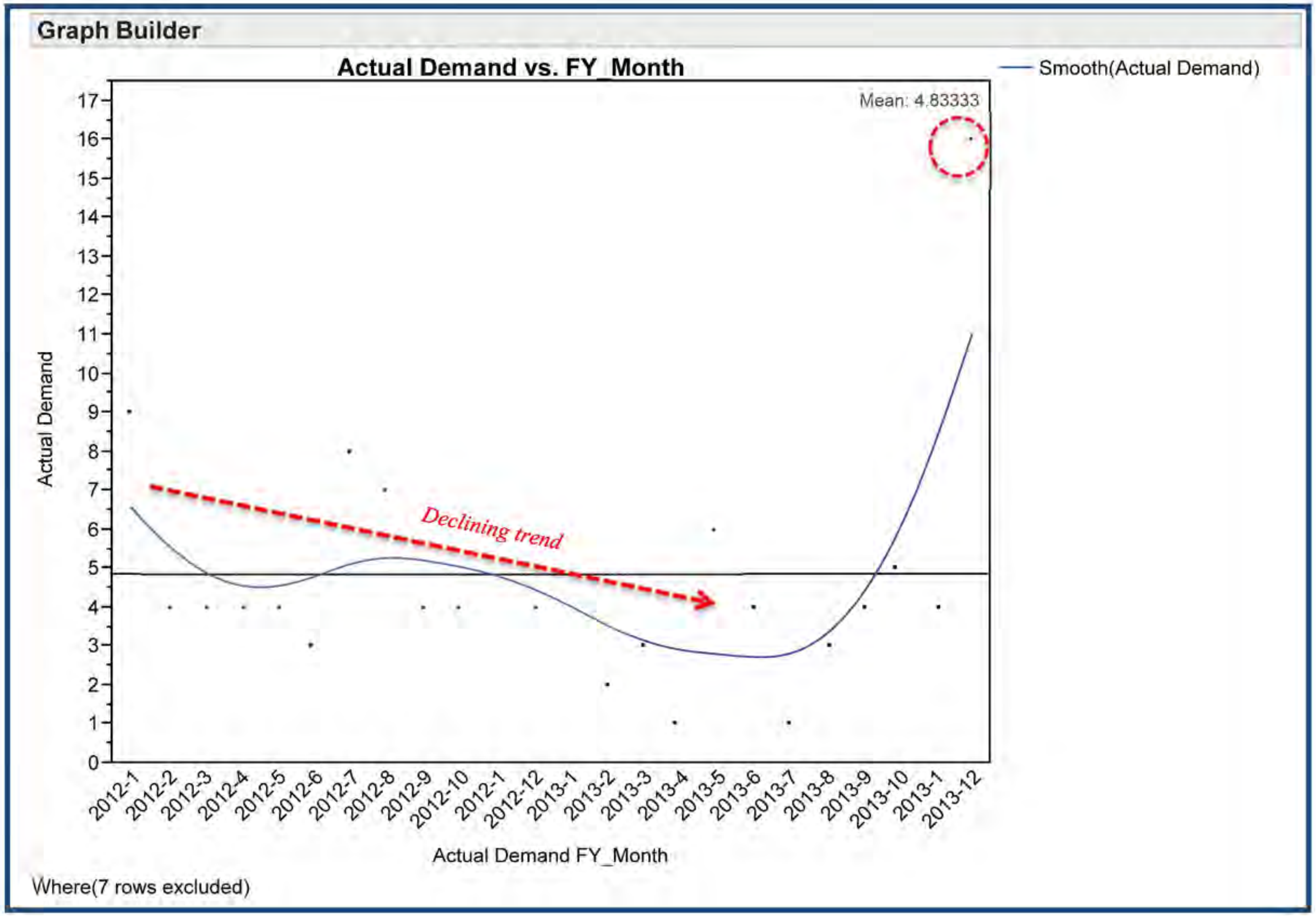

Figure 4. Actual Demand by Month (SAS, 2012, p. 50)

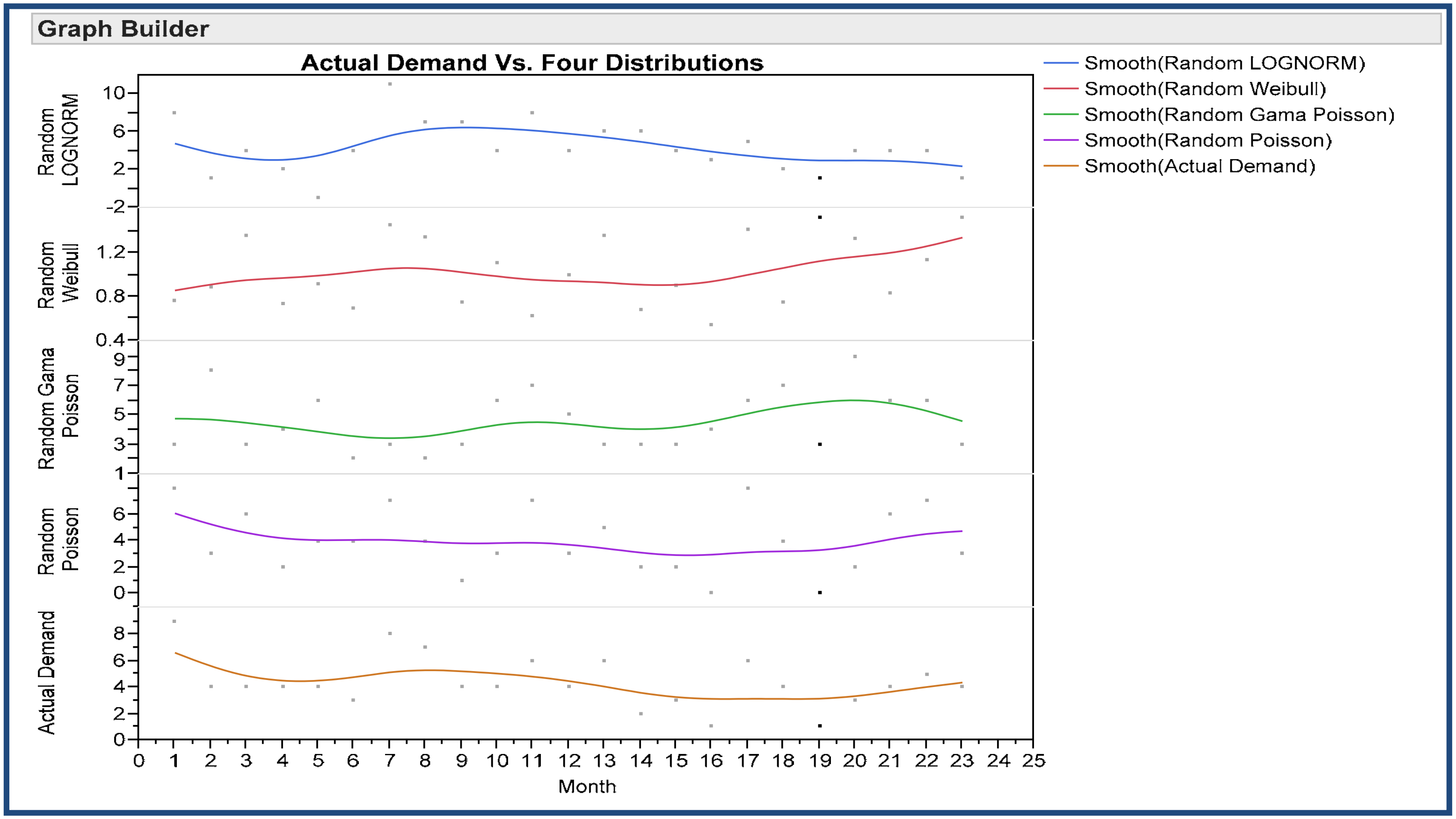

Figure 5. Actual Demand versus Four Probability Distributions (SAS, 2012, p. 50)

D. DESCRIPTION AND USE OF GOODNESS OF FIT FOR PROBABILITY DISTRIBUTIONS

The goodness-of-fit functions in both the JMP and Crystal Ball software analyze the raw data set (e.g., product demand quantity over a period of time, such as demand quantity during individual months from October 2010 to September 2013). The analyses and tests produce a list of probability distributions sorted by most likely (best goodness of fit) to least likely probability distributions. Therefore, the goodness-of-fit tests used in this research are Empirical Distribution Function Tests derived from actual product demand data. After testing various distributions for goodness of fit, the probability distribution with the highest p-value is used in our forecast models (SAS, 2012).

We used JMP to calculate distributional probability expectations using goodness-of-fit tests (i.e., hypothesis test), in which "the null hypothesis is that two distributions are identical (i.e., that they fit one another)." A goodness-of-fit test rejects the hypothesis based on a criterion score that if $p < .05$ then reject the null hypothesis.

However, unlike typical hypothesis tests, in a goodness-of-fit test, one is typically hoping *not* to reject the null hypothesis. Unlike most hypothesis tests, low p-values in these tests are bad, because they denote less evidence supporting the null hypothesis. Therefore, the higher p-values are better in this case because they denote more evidence supporting the null hypothesis (Doerr, 2014)

In JMP the best-fit distributions are listed in descending order by *p values* and by *ascending order* (lowest value is best distribution fit). Distribution fit is established by calculating the p-value score, the corrected Akaike information criterion (AIC) (Akaike, 1987) as well as other statistical criterion built into the JMP software.

First, AIC is the degree of the unsuitability of fit in a model defined by a natural logarithm score where the lower the AIC score, the better the goodness of fit of the probability distribution model (Akaike, 1987). "However, the AIC model is very sensitive to sample size and the introduction of an increasing number of factors causes increased randomness (bias or noise), which significantly decreases the model accuracy" (Akaike, 1987, p. 318). The AIC is calculated as follows:

AIC = (-2) log maximum likelihood + 2 (number of parameters)

Second, among the AIC and the AIC_C models, the bias of the latter is usually drastically lesser than that of the former. "Even in modest sample sizes, AIC_C offers significantly better model options than AIC" (Hurvich & Tsai, 1991).

Although JMP provided various calculations for goodness of fit, the easiest to use to identify the best goodness of fit distribution was the p-value criterion.

Additionally, we used actual product demand as a raw input and the best goodness-of-fit probability distribution was used for each NIIN (stock item) to run a Monte Carlo simulation with 100,000 trials, which resulted in a demand forecast as well as a conditional value at risk analysis (stock-out risk analysis). See Chapter IV for detailed explanation about Monte Carlo simulations.

- **Probability Distributions**

Next, we define various probability distributions according to both the Crystal Ball and JMP Pro 10 User Manuals (verbatim).

a. Normal Distribution

The normal distribution is a continuous probability distribution that uses mean and standard deviation as parameters (Oracle, 2014). As described in the Oracle Crystal Ball manual, "The Normal Distribution is frequently applied to model measures that are symmetric, with the majority of the values located along the center of the curve" (Oracle, 2014, p. 219). Figure 6 depicts a normal distribution.

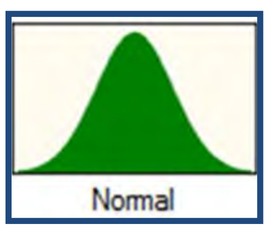

Figure 6. Normal Distribution

b. Lognormal Distribution

As described in the Oracle User's manual, "The lognormal is a continuous probability distribution that is generally applied in circumstances where values are positively skewed, while the majority of the values are located near the minimum value" (Oracle, 2014, p. 215). The parameters for the lognormal distribution are mean and standard deviation. Figure 7 depicts the lognormal distribution.

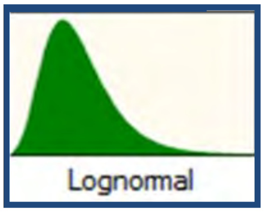

Figure 7. Lognormal Distribution

c. Weibull Distribution

The Oracle manual describes the Weibull distribution as follows:

Weibull distribution is a continuous probability distribution. The parameters for the Weibull distribution are location, scale, and shape (Oracle, 2014, p. 225). Figure 8 depicts the Weibull distribution.

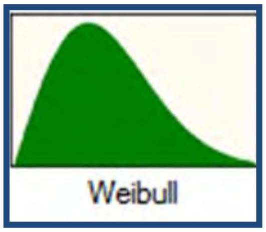

Figure 8. Weibull Distribution

d. Exponential Distribution

The exponential distribution is a continuous probability distribution with rate as the parameter (Oracle, 2014), as shown in Figure 9.

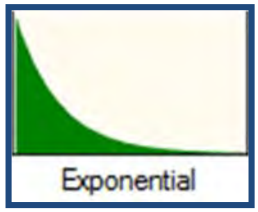

Figure 9. Exponential Distribution

e. The Binomial Distribution

The binomial distribution, depicted in Figure 10, is a discrete probability distribution that describes the quantity of successes in a fixed number of trials (e.g., the occurrence of heads in 10 flips of a coin). The parameters for a binomial distribution are probability and number of trials (Oracle, 2014).

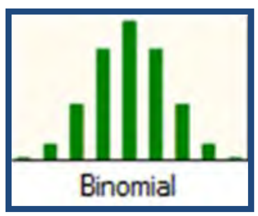

Figure 10. Binomial Distribution

f. Poisson Distribution

The Poisson distribution, shown in Figure 11, is a discrete probability distribution with rate as the parameter (Oracle, 2014).

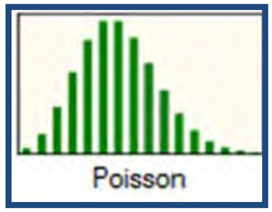

Figure 11. Poisson Distribution

g. Negative Binomial Distribution

The negative binomial distribution is a discrete probability distribution with the following parameters: probability and shape (Oracle, 2014). Figure 12 depicts the negative binomial distribution.

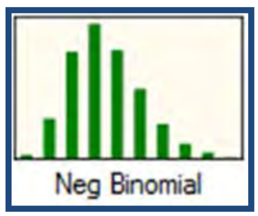

Figure 12. Negative Binomial Distribution

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III. PROJECT METHODOLOGY

This chapter discusses project methodology, a compilation of the following points:

A. Facts
B. Assumptions
C. Summary of FY2010 To FY2013 Aviation Supply Chain
D. Inventory classification
E. Focus of research: Class A inventory
F. Statistical analysis of historical product demand
G. Lead time demand forecast: An input for inventory policy
H. Conditional value at risk
I. Inventory policy formulation

A. FACTS

This research involves a quantitative analysis of the historical demand for the Defense Logistics Agency (DLA) aviation supply chain stock items. Qualitative analysis is a forgone opportunity due to the shortage in many scarce resources: labor hours, lack of insider/expert/heuristic knowledge, which would require involvement from specialists across the DLA organization, from inventory managers to forecasters to strategic planners, as well as contracting and finance personnel.

The DLA’s FY2013 management objective for forecast accuracy was 60%.

B. ASSUMPTIONS

- Quantitative analysis of demand can help improve both forecast accuracy and target fill rates above the DLA’s FY2013 management objective.
- For the purpose of this research, selling price is used in lieu of cost throughout our analysis.

- Most importantly, we hypothesize that probability distributions describe product demand patterns and can be used as an effective forecasting technique.

C. SUMMARY OF FY2010 TO FY2013 AVIATION SUPPLY CHAIN

In order to start the process of understanding the impact of individual stock items sales on annual revenue, we first introduce a summary Table 1 containing DLA aviation-supply-chain annual revenue and quantity of inventory items ordered during FY2010 to FY2013. Notice that annual revenue was much less in FY2013:

	Revenue	qty_req
FY	Sum	Sum
2010	$2,692,055,593	24,139,182
2011	$3,145,200,422	23,675,167
2012	$3,323,996,371	21,721,754
2013	$2,600,361,361	17,904,558

Table 1. DLA Supply Chain Revenue FY2010–FY2013

Over the four fiscal years observed, the top 10 percent of total NIINs accounted for more than 70 percent of the total annual revenues identified in DLA's Aviation Supply Chain. The NIINs that make up the top 10 percent are not a constant list. They rotate in and out as an annual turnover of NIINs that rank in the top 10 percent. Therefore, the top 10 percent list must be updated annually. For example, using FY10 as the base year, Figure 13 displays the NIINs that survive from year to year in that top 10 percent category. We will categorize these top 10 percent as Class A NIIN's, a term commonly used in the ABC classification method.

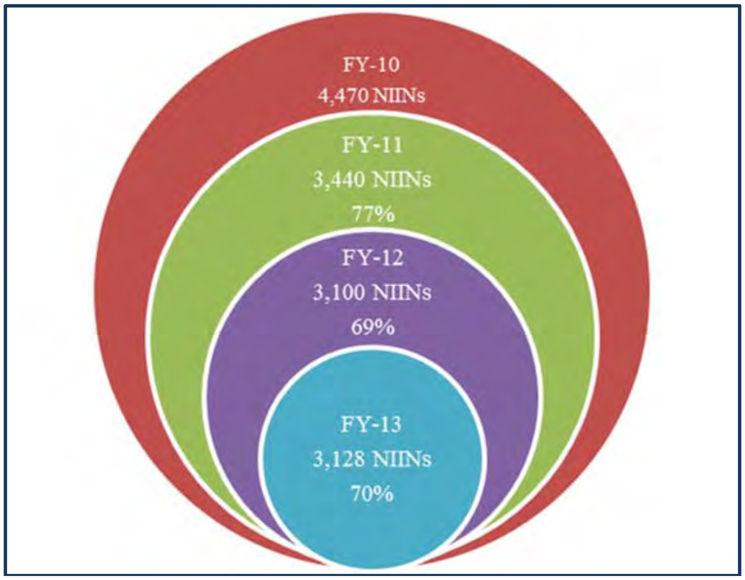


Figure 13. FY10 to FY13 NIIN Survivability Illustration

D. INVENTORY CLASSIFICATION: ABC CLASSIFICATION METHOD

The ABC classification process should be conducted at the end of each fiscal year. This classification method begins by ranking in descending order the NIINs by annual revenue each NIIN generated during the previous fiscal year. The NIIN that generated the highest revenue is ranked number 1 (lowest rank represents highest impact on annual revenue). All aviation-supply-chain stock items ranked. The purpose of this task is to identify the top 10% of NIINs (JMP software was used to consolidate revenue values). When FY2013 ended, it was determined that the top 10% of NIINs accounted for almost 80% of total annual revenue (discussed in more detail in subsequent paragraphs).

- **Step 1: Organize and Consolidate**

Input the previous fiscal year data in a JMP table (daily demand data). For this research, data from FY2013 is used as shown in Figure 14.

- **Step 2: Create a Summary List**

Use JMP software to create a summary list as shown in Figure 15 that aggregates daily demand into both annual revenue and product demand quantity per NIIN (this research consolidated the revenue values of over one million FY2013 records into 55,000

records by NIIN using a single JMP table). At the top of the screen, select “Tables” and then “Tabulate.” Drag the variables from the select Column box and drop in the Statistics/Group boxes on the right. Variables that become records (for example, Date, NIIN, NAME) need to be dropped in the “drop zone for rows”. Numeric variables that need to be aggregated should be dragged to the box, “drop zone for columns” (for example, demand quantity and Price).

- **Step 3: Generate a New Table**

In Step 3, JMP generates a new table containing the variables shown in Figure 16. From the tabulate menu, click on “create data table”.

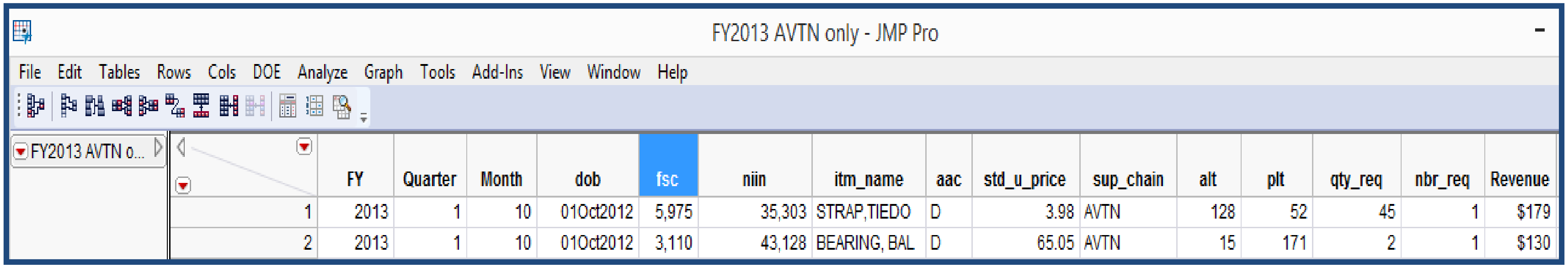
The columns can then be reorganized from left to right, as desired using the “Cols” menu as shown in figure 16.

- **Step 4: Produce an Actionable List**

The next step is to produce a list that identifies which stock items warrant the greatest priority and allocation of labor hours. These are the items with the highest impact on annual revenue, known as Class-A NIINs. This is accomplished by sorting inventory items, in descending order, according to the annual revenue column. Create additional columns as specified below and classify stock as class A, B, or C:

- Sort in JMP, high to low revenue
- Add column “% Total Revenue”
- Add column “Cumulative %”

Classify ABC (10%, 40%, 50% respectively). Top 10% of total NIINs (i.e., top 10 out of 100 NIINs) with the highest revenue receive Class-A designation, Class B is the next 40% of stock items, and Class-C is the remaining 50% of stock. JMP generated a new table containing 55,000 records. Below are two screenshots of that table with the three newly added columns. Notice that in the classification column, Class-A items are the top 5,500 records. An extract of Class-A items is displayed in Figure 17.



	FY	Quarter	Month	dob	fsc	niin	itm_name	aac	std_u_price	sup_chain	alt	plt	qty_req	nbr_req	Revenue
1	2013	1	10	01Oct2012	5,975	35,303	STRAP,TIEDO	D	3.98	AVTN	128	52	45	1	$179
2	2013	1	10	01Oct2012	3,110	43,128	BEARING, BAL	D	65.05	AVTN	15	171	2	1	$130

Figure 14. Step 1, Part A

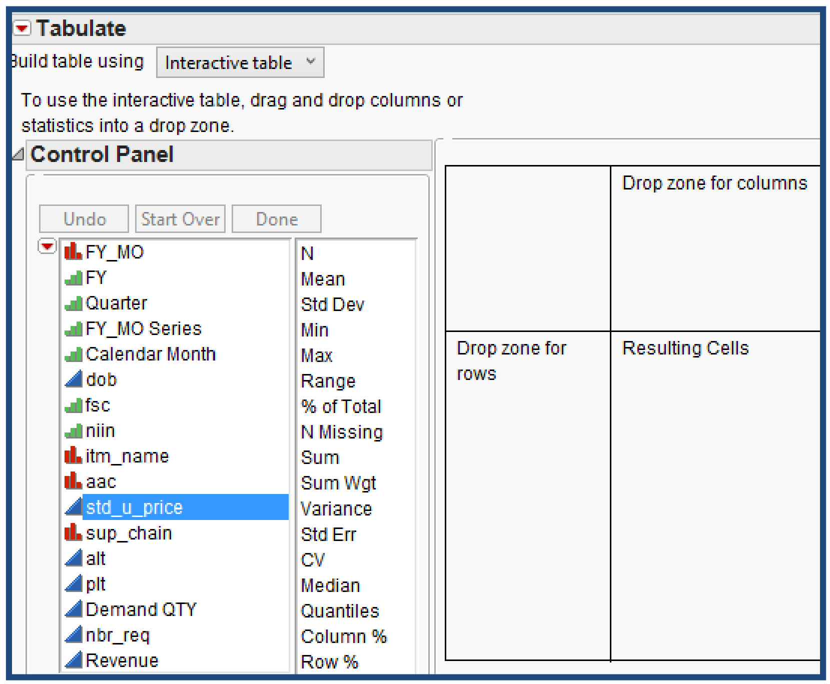


Figure 15. Step 2, Part A

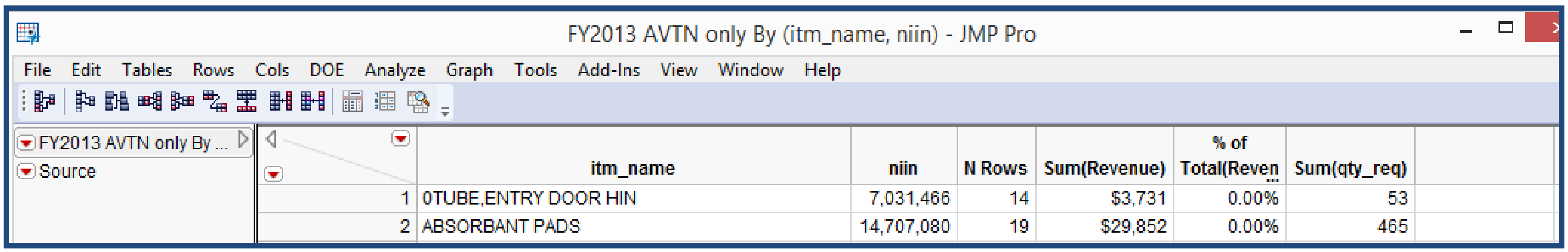


Figure 16. Step 3, Part A

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FY2013 master ABC classification list - JMP Pro

File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help

FY2013 master ABC c...

Source

	itm_name	niin	N Rows	Sum(qty_req)	Sum(Revenue)	% of Total(Revenue)	Cumulative %	Classification
1	STABILIZER,VERTICAL	015251263	28	55	$42,061,925	1.61754%	1.61754%	A
2	BLADE,TURBINE ROTOR	014634340	108	5,166	$21,690,157	0.83412%	2.45166%	A
3	THERMOCOUPLE,CONTAC	015075310	247	24,603	$17,724,312	0.68161%	3.13327%	A
5496	COUPLING,TUBE	010901408	66	370	$87,367	0.00336%	76.33928%	A
5497	RETAINER,SPECIAL	012892457	3	315	$87,362	0.00336%	76.34264%	A
5498	DIAPHRAGM ASSEMBLY,VALVE	007873860	29	100	$87,359	0.00336%	76.34600%	A
5499	PISTON,LINEAR ACTUA	013564617	7	44	$87,357	0.00336%	76.34936%	A
5500	INDICATOR,HUMIDITY,	006181822	103	1,468	$87,337	0.00336%	76.35272%	A
5501	BEARING,PLAIN,SPHERICAL	011572645	64	387	$87,310	0.00336%	76.35608%	B
5502	PLUG,SIGHT GLASS	013089451	90	535	$87,304	0.00336%	76.35944%	B

Figure 17. Step 4, Part A

- **Step 5: Simplify**

The new list of 55,000 records can then be further simplified on a summary table or graph in order to present this information to stakeholders. Segregating the few NIINs that have the greatest impact on the DLA annual budget:

Produce a "Tabulate" Table.

In JMP, at the top of the screen in the "Tables" menu, select "Tabulate." Drag and drop the variables from the box on the left to the box on the right. Table 2 displays an FY2013 tabulate table (in progress). Notice 5,500 NIINs are Class A stock and make up ~76 percent of total revenue in the Aviation Supply Chain, or nearly $2 billion in revenue (FY2013). Class B and Class C stock fall way behind in total revenue:

Tabulate

Control Panel

To add to the table, drag and drop columns or statistics into the column header or row label area of the table.

itm_name	N
niin	Mean
N Rows	Std Dev
Sum(qty_req)	Min
Sum(Revenue)	Max
% of Total(Revenue	Range
Cumulative %	% of Total
Classification	N Missing
	Sum
	Sum Wgt
	Variance
	Std Err
	CV
	Median
	Quantiles
	Column %
	Row %
	All

☐ Include missing for grouping columns
☐ Order by count of grouping columns

	Sum(Revenue)	Sum(Revenue)	% of Total(Revenue)	Sum(qty_req)	
Classification	N	Sum	Sum	Sum	% of Total
A	5,500	$1,985,446,199	76.35270%	5,343,933	9.99%
B	22,000	$565,527,696	21.74804%	7,497,720	39.98%
C	27,529	$49,387,466	1.89925%	5,062,905	50.03%

Table 2. Step 5, Part A.

Relatively few stock items account for most of DLA Aviation Supply Chain revenue; 5,500 NIINs (out of 55,029) were selected to make up Class A NIINs. This is graphically displayed in Figure 18. Here Class A represents the top 10% of total NIIN count, which makes up about 76% of the total Revenue for FY2013.

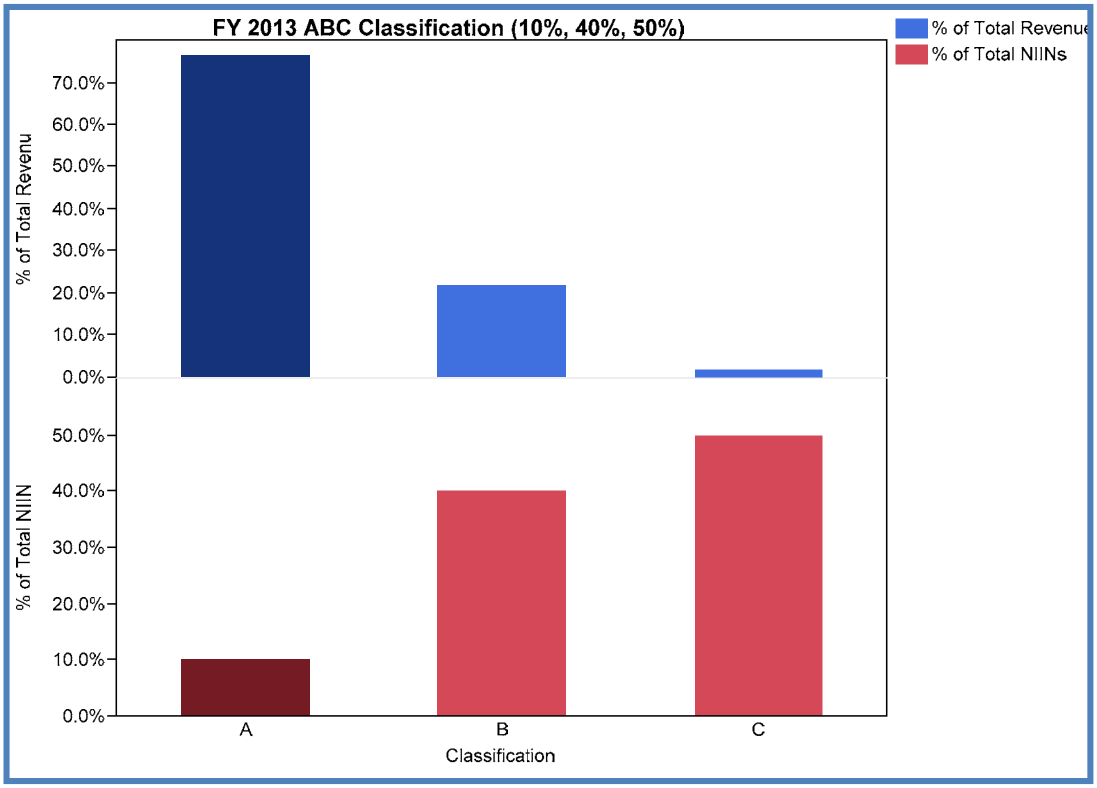


Figure 18. FY13 ABC Classification

The same process discussed above is applied to FY 2012 demand data as shown in Table 3.

Tabulate

Control Panel

To add to the table, drag and drop columns or statistics into the column header or row label area of the table.

% of Total(Revenue)	N
Cumulative %	Mean
Cumulative % 2	Std Dev
Cumulative % 3	Min
niin	Max
N Rows	Range
Sum(Revenue)	% of Total
% of Total(Revenue)	N Missing
Sum(qty_req)	Sum
Cumulative % 4	Sum Wgt
Classification	Variance
	Std Err
	CV
	Median
	Quantiles
	Column %
	Row %
	All

☐ Include missing for grouping columns

☐ Order by count of grouping columns

Classification	Sum(Revenue) N	Sum(Revenue) Sum	% of Total	Sum(qty_req) Sum	% of Total(Revenue) Sum
A	5,300	$2,641,353,828.00	10.18%	6,595,381	79%
B	20,700	$625,539,414.00	39.76%	9,184,835	19%
C	26,066	$57,103,491.00	50.06%	5,941,538	2%

Table 3. FY12 Tabulate: Top 10% (5,300 NIINs ~ 79% of Total

Revenue)

Figure 19 shows that Class A NIINs represent 79% of Total Revenue in FY2012.

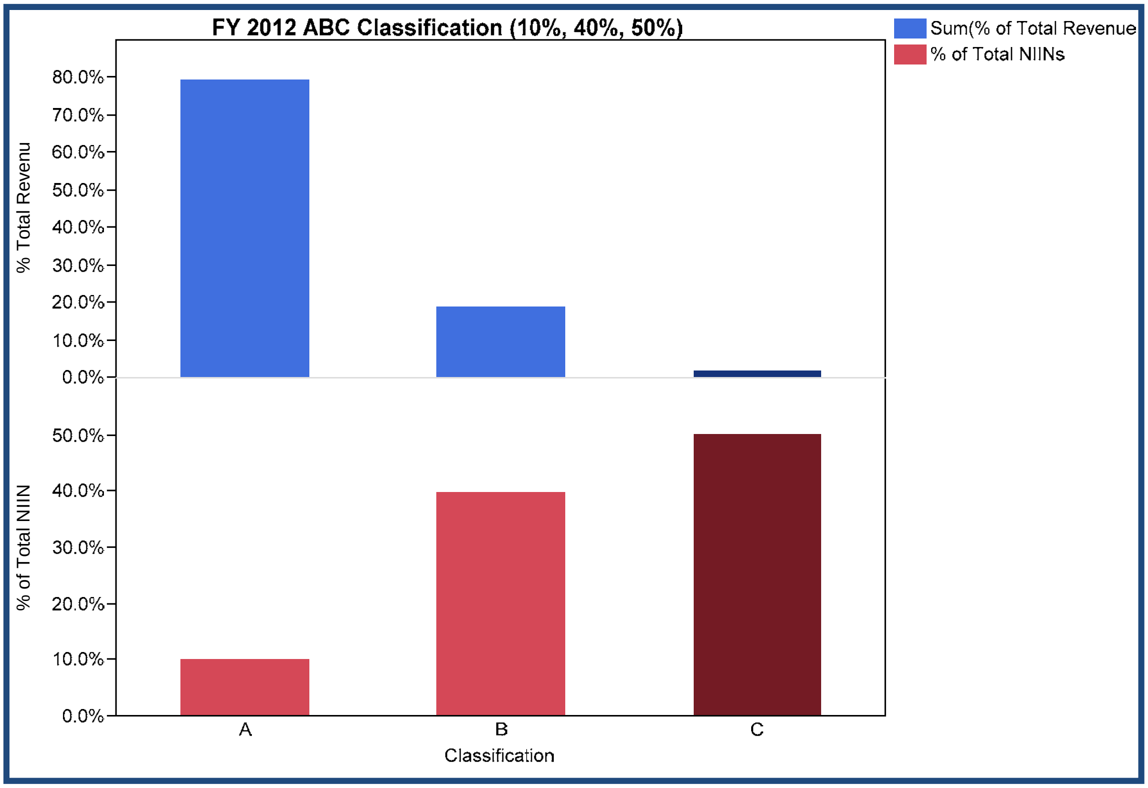


Figure 19. FY12 ABC Classification

The process is repeated for FY2011 as shown in Table 4.

Tabulate

Control Panel

To add to the table, drag and drop columns or statistics into the column header or row label area of the table.

itm_name	N
niin	Mean
N Rows	Std Dev
Sum(Revenue)	Min
% of Total(Revenue	Max
Sum(qty_req)	Range
Cumulative %	% of Total
Classification	N Missing
	Sum
	Sum Wgt
	Variance
	Std Err
	CV
	Median
	Quantiles
	Column %
	Row %
	All

☐ Include missing for grouping columns

☐ Order by count of grouping columns

		Sum(Revenue)			Sum(qty_req)	% of Total(Revenue)
Classification	N	Sum	% of Total	N	Sum	Sum
A	4,800	$2,407,495,613.00	9.98%	4,800	7,508,884	76.545061980%
B	19,200	$674,029,984.00	39.92%	19,200	9,911,220	21.430427460%
C	24,102	$63,675,170.00	50.11%	24,102	6,255,063	2.024510780%

Table 4. FY11 Tabulate: Top 10% (4,800 NIINs ~ 77% of Total Revenue)

Figure 20 shows that Class A NIINs represent 77% of Total Revenue in FY2011.

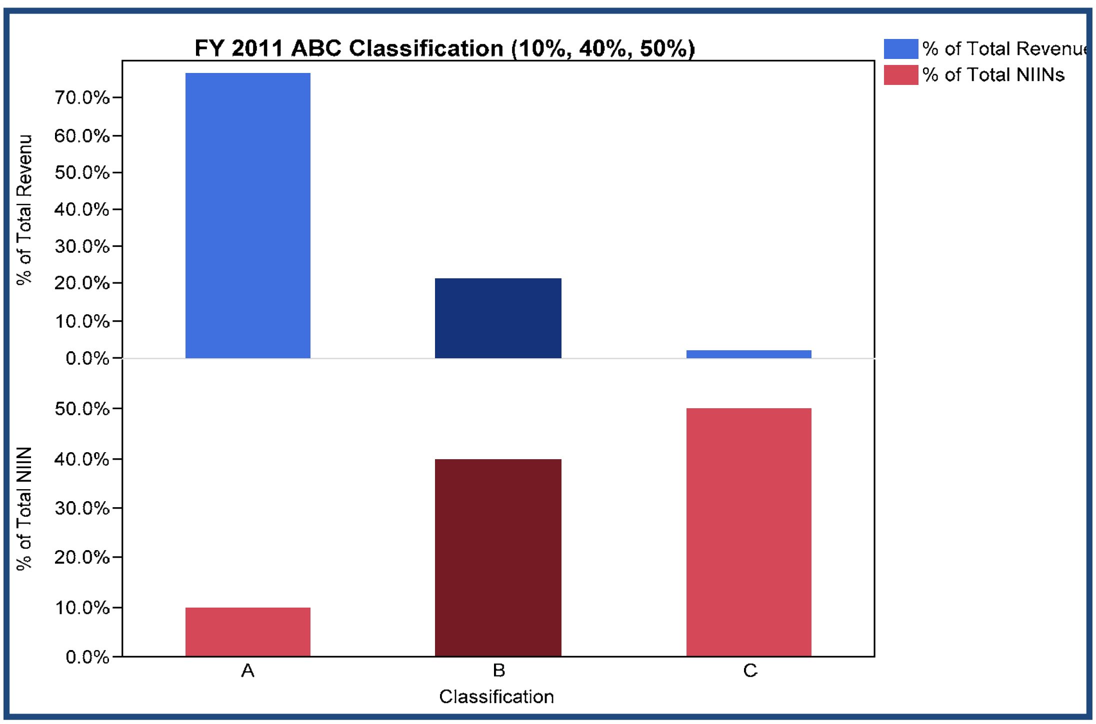
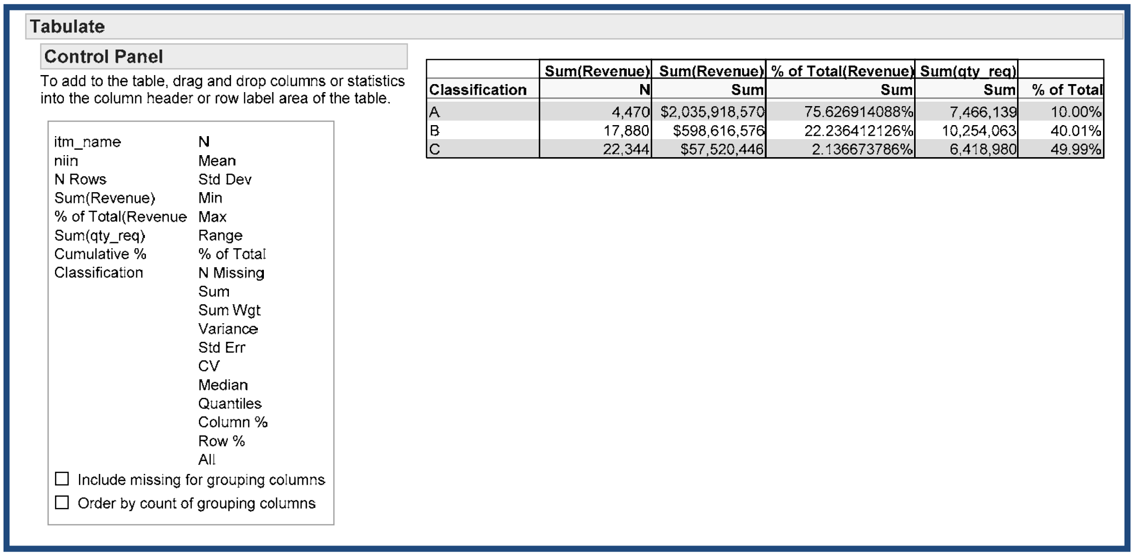


Figure 20. FY11 ABC Classification

The process is repeated for FY2010 as shown in Table 5.



	Sum(Revenue)	Sum(Revenue)	% of Total(Revenue)	Sum(qty_req)	
Classification	N	Sum	Sum	Sum	% of Total
A	4,470	$2,035,918,570	75.626914088%	7,466,139	10.00%
B	17,880	$598,616,576	22.236412126%	10,254,063	40.01%
C	22,344	$57,520,446	2.136673786%	6,418,980	49.99%

Table 5. FY10 Tabulate: Top 10%, (4,470 NIINs ~ 76% of Total Revenue)

Figure 21 shows that Class A NIINs represent 76% of Total Revenue in FY 2010.

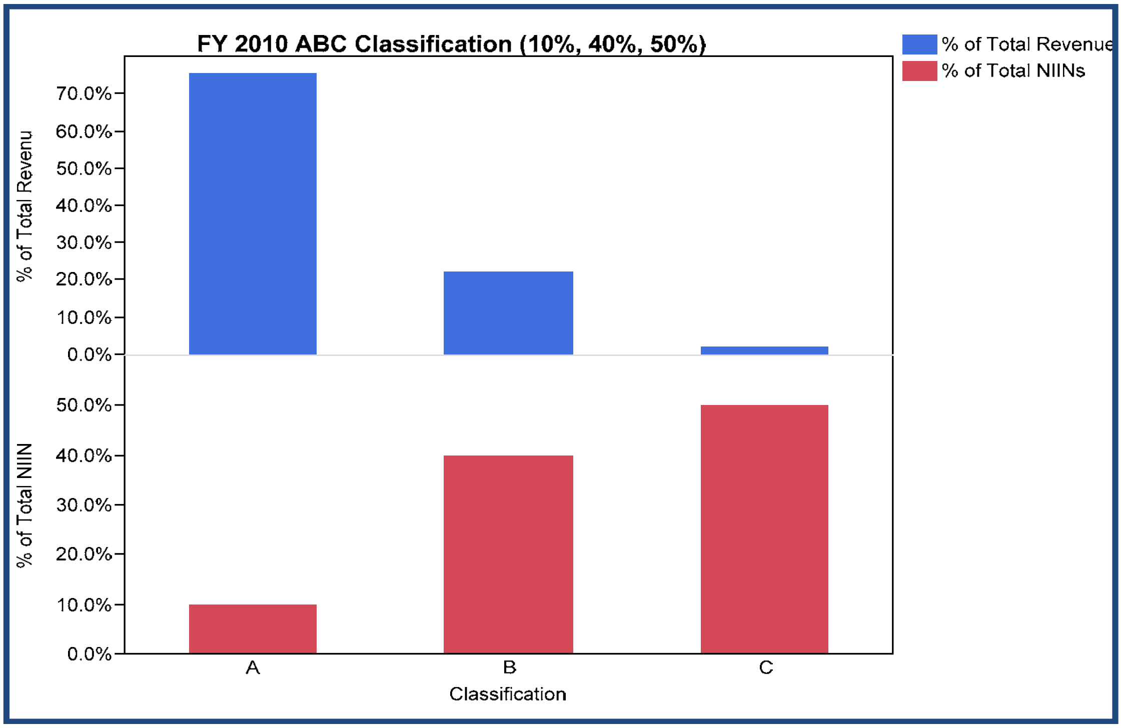


Figure 21. FY 10 ABC Classification

E. FOCUS OF THIS RESEARCH: CLASS A NIINS OF FY2013 (5,500 NIINS)

Focusing the effort of this research on Class A NIINs has the benefit of segregating the few stock items with the greatest impact on the budget from the many with the least impact: Class-A stock accounts for approximately 80% of annual revenue in FY2013 (rounded up from 76%). Refer to Exhibit A for a list of ABC classification by NIIN.

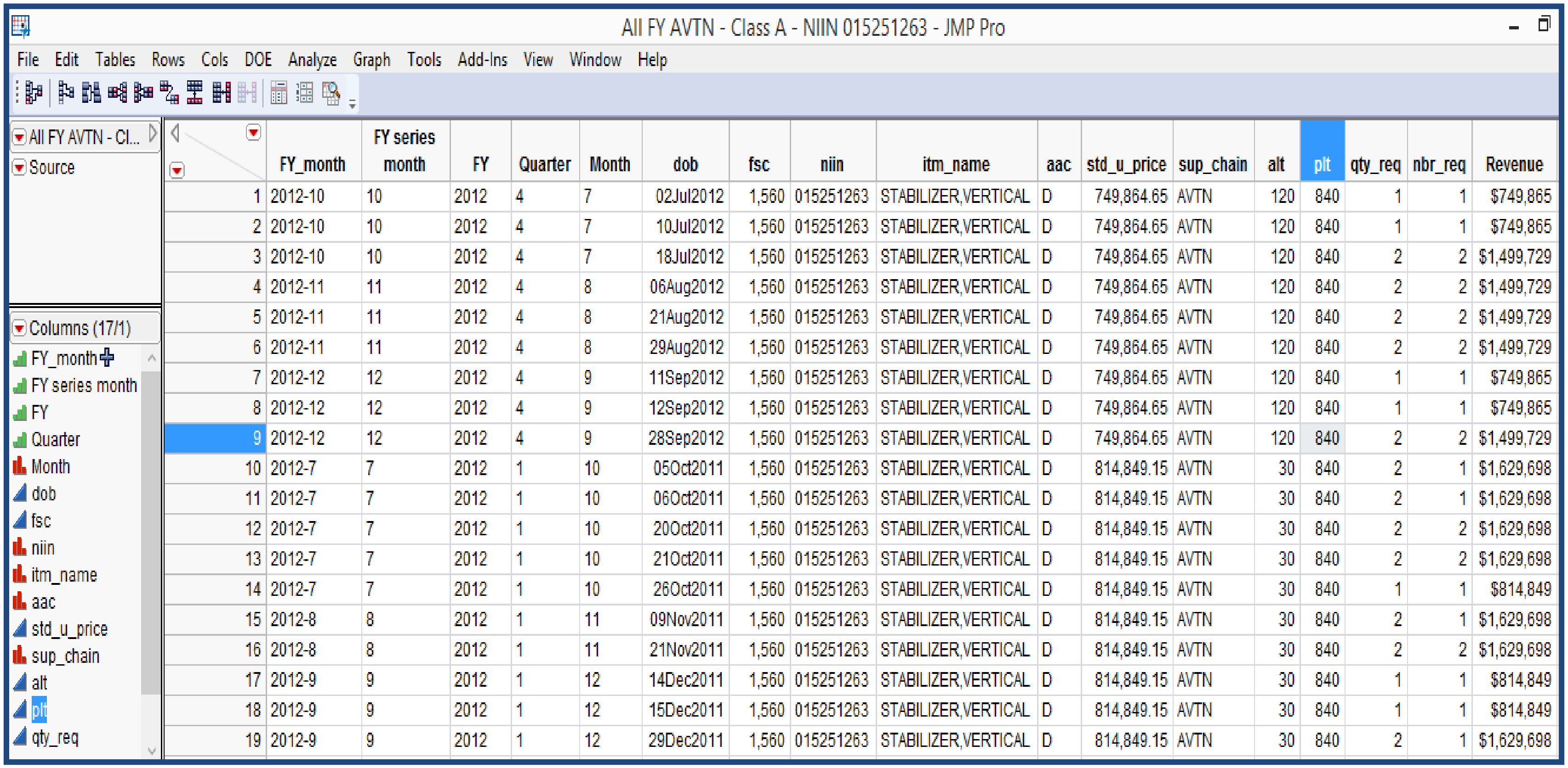
F. STATISTICAL ANALYSIS OF HISTORICAL PRODUCT DEMAND

This section is devoted to demonstrating how a single NIIN is processed for historical demand analysis. To demonstrate the statistical analysis steps, we use NIIN 015251263, Vertical Stabilizer only as an example in steps 1 to 7 below.

- **Step 1: Add Columns For Organizing Data in Time-Series**

Designating time series order for the product demand data is accomplished through a variety of means. When analyzing data from a single fiscal year, the simplest

and perhaps most practical format is the "FY series month" format, which assigns a numerical value to a month based on its order on the fiscal year. For example, whereas the month of October has a numerical value of 1, the month of September has a numerical value of 12. Therefore, this implies that fiscal year monthly demand data is assigned FY_MO format, such as 2012_1 for October 2011 and 2012_12 for September 2012. Similarly, when analyzing data across fiscal years, the most practical format is the "month" column, which assigns an ascending numerical value to each month. For example, in a time span of 24 months, whereas October 2011 would be assigned a numerical value of "1," September 2013 would be assigned a numerical value of "24." Figure 22 shows the first step of data organized in a time series. Although not shown in Figure 22, no gaps must exist in the time series. That is, a missing month, due to zero demand should be added to the table so that it is a seamless timeline in order to generate accurate statistical values. Clearly, missing months as shown in Figure 22 would generate incorrect mean and standard deviation values.



	FY_month	FY series month	FY	Quarter	Month	dob	fsc	niin	itm_name	aac	std_u_price	sup_chain	alt	plt	qty_req	nbr_req	Revenue
1	2012-10	10	2012	4	7	02Jul2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
2	2012-10	10	2012	4	7	10Jul2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
3	2012-10	10	2012	4	7	18Jul2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
4	2012-11	11	2012	4	8	06Aug2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
5	2012-11	11	2012	4	8	21Aug2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
6	2012-11	11	2012	4	8	29Aug2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
7	2012-12	12	2012	4	9	11Sep2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
8	2012-12	12	2012	4	9	12Sep2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
9	2012-12	12	2012	4	9	28Sep2012	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
10	2012-7	7	2012	1	10	05Oct2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698
11	2012-7	7	2012	1	10	06Oct2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698
12	2012-7	7	2012	1	10	20Oct2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	2	$1,629,698
13	2012-7	7	2012	1	10	21Oct2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	2	$1,629,698
14	2012-7	7	2012	1	10	26Oct2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	1	1	$814,849
15	2012-8	8	2012	1	11	09Nov2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698
16	2012-8	8	2012	1	11	21Nov2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	2	$1,629,698
17	2012-9	9	2012	1	12	14Dec2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	1	1	$814,849
18	2012-9	9	2012	1	12	15Dec2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	1	1	$814,849
19	2012-9	9	2012	1	12	29Dec2011	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698

Figure 22. Demand Data Organized by Time Series

- **Step 2: Create a Tabulate Table in JMP for Monthly Demand, Admin Lead Time (alt) and Procurement Lead Time (plt)**

Click on the Tables menu at the top of the screen. Select Tabulate. Drag and drop variables:

- Row: FY_QTR, FY_month, NIIN
- Columns: qty_req, revenue (when pop-up window appears, select "analysis")
- Columns: Admin Lead Time (alt) and Procurement Lead Time (plt), when pop-up window appears, select "group"

Note: By including the "alt" and "plt" columns, new relationships are revealed. Notice that the both the Admin Lead Time and Procurement Lead Time change across fiscal years. *This is an opportunity to identify areas for improving lead time, which could potentially lead to reduction in inventory costs (as discussed in chapters IV and V).* Table 6 illustrates the product from Step 2.

Tabulate

Control Panel

To add to the table, drag and drop columns or statistics into the column header or row label area of the table.

FY_QTR	N
FY_month	Mean
FY series month	Std Dev
FY	Min
Quarter	Max
Month	Range
dob	% of Total
fsc	N Missing
niin	Sum
itm_name	Sum Wgt
aac	Variance
std_u_price	Std Err
sup_chain	CV
alt	Median
plt	Quantiles
qty_req	Column %
nbr_req	Row %
Revenue	All

☐ Include missing for grouping columns
☐ Order by count of grouping columns

			qty_req	Revenue	alt				plt		
niin	FY_QTR	FY_month	Sum	Sum	30	84	90	120	540	840	999
015251263	2010-1	2010-9	1	$644,656	0	0	1	0	0	0	1
	2011-2	2011-5	1	$833,497	1	0	0	0	1	0	0
		2011-6	2	$1,666,994	2	0	0	0	2	0	0
	2011-4	2011-11	1	$814,849	1	0	0	0	0	1	0
	2012-1	2012-7	9	$7,333,642	5	0	0	0	0	5	0
		2012-8	4	$3,259,397	2	0	0	0	0	2	0
		2012-9	4	$3,259,397	3	0	0	0	0	3	0
	2012-2	2012-4	4	$3,145,318	1	0	0	0	0	1	0
		2012-5	4	$3,145,318	2	0	0	0	0	2	0
		2012-6	3	$2,358,988	2	0	0	0	0	2	0
	2012-3	2012-7	8	$6,290,635	5	0	0	0	0	5	0
		2012-8	7	$5,504,306	3	0	0	0	0	3	0
		2012-9	4	$3,145,318	2	0	0	0	0	2	0
	2012-4	2012-10	4	$2,999,459	0	0	0	3	0	3	0
		2012-11	6	$4,499,188	0	0	0	3	0	3	0
		2012-12	4	$2,999,459	0	0	0	3	0	3	0
	2013-1	2013-7	6	$4,499,188	0	3	0	0	0	3	0
		2013-8	2	$1,499,729	0	1	0	0	0	1	0
		2013-9	3	$2,249,594	0	2	0	0	0	2	0
	2013-2	2013-4	1	$749,865	0	1	0	0	0	1	0
		2013-5	6	$4,499,188	0	3	0	0	0	3	0
		2013-6	4	$2,999,459	0	2	0	0	0	2	0
	2013-3	2013-7	1	$749,865	0	1	0	0	0	1	0
		2013-8	3	$2,249,594	0	2	0	0	0	2	0
		2013-9	4	$2,999,459	0	2	0	0	0	2	0
	2013-4	2013-10	5	$3,913,197	0	2	0	0	0	2	0
		2013-11	4	$3,130,558	0	2	0	0	0	2	0
		2013-12	16	$12,522,231	0	7	0	0	0	7	0

Table 6. Step 2, Part B

- **Step 3: Make Data Table**

Click on the red triangle next to Tabulate. Select Make into Data Table as shown in Table 7.

- **Step 4: Use Data Table to Create Graphs**

Consider converting the “Tabulate” data table as shown in Tables 7 to 9 into a summary table that can be used to create graphs that show demand trend. Simple graphs can convey powerful ideas that help accelerate understanding of demand volume and demand patterns. See Figures 24 to 26 for examples.

- **Step 5: Build a Graph.**

From the menu at the top of the page, click on “Graph.” Select “Graph Builder,” as illustrated in Table 9.

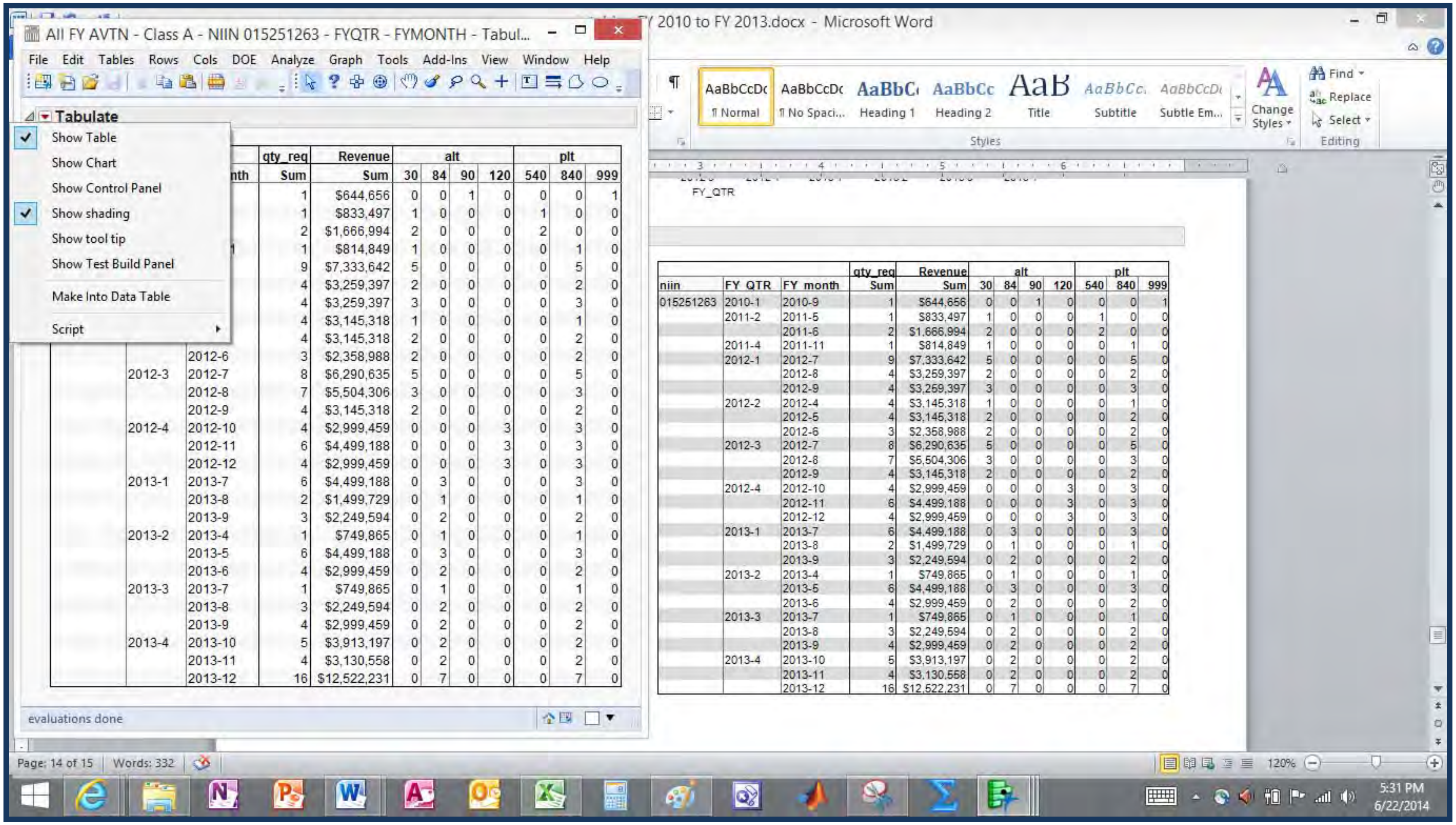


Table 7. Step 3, Part B

	FY_QTR	FY_month	fsc	niin	itm_name	aac	std_u_price	sup_chain	alt	plt	qty_req	nbr_req	Revenue
1	2012-4	2012-10	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
2	2012-4	2012-10	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
3	2012-4	2012-10	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
4	2012-4	2012-11	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
5	2012-4	2012-11	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
6	2012-4	2012-11	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
7	2012-4	2012-12	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
8	2012-4	2012-12	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	1	1	$749,865
9	2012-4	2012-12	1,560	015251263	STABILIZER,VERTICAL	D	749,864.65	AVTN	120	840	2	2	$1,499,729
10	2012-1	2012-7	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698
11	2012-1	2012-7	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698
12	2012-1	2012-7	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	2	$1,629,698
13	2012-1	2012-7	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	2	$1,629,698
14	2012-1	2012-7	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	1	1	$814,849
15	2012-1	2012-8	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698
16	2012-1	2012-8	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	2	$1,629,698
17	2012-1	2012-9	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	1	1	$814,849
18	2012-1	2012-9	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	1	1	$814,849
19	2012-1	2012-9	1,560	015251263	STABILIZER,VERTICAL	D	814,849.15	AVTN	30	840	2	1	$1,629,698
20	2012-2	2012-4	1,560	015251263	STABILIZER,VERTICAL	D	786,329.43	AVTN	30	840	4	4	$3,145,318
21	2012-2	2012-5	1,560	015251263	STABILIZER,VERTICAL	D	786,329.43	AVTN	30	840	2	2	$1,572,659

Table 8. Step 4, Part B

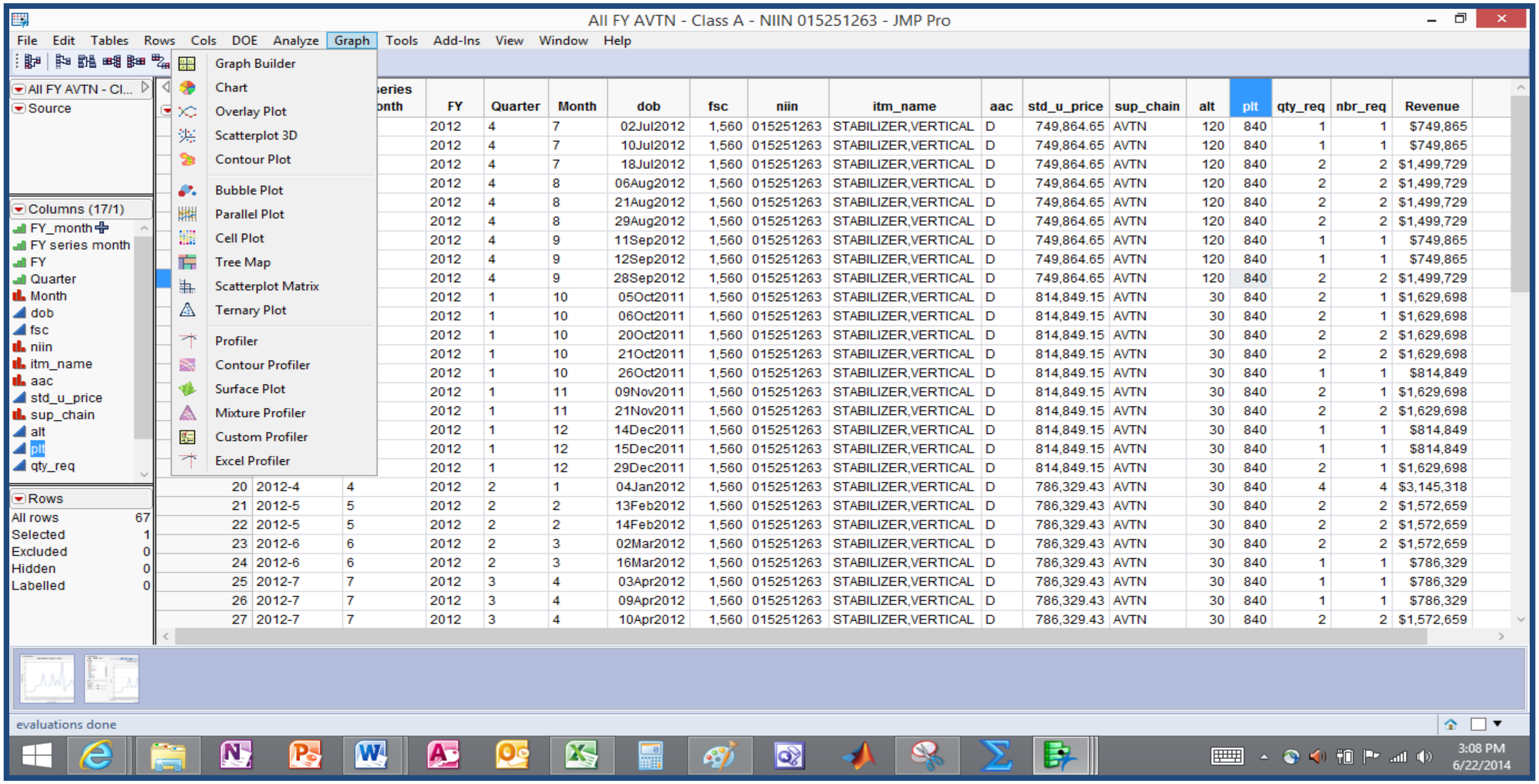
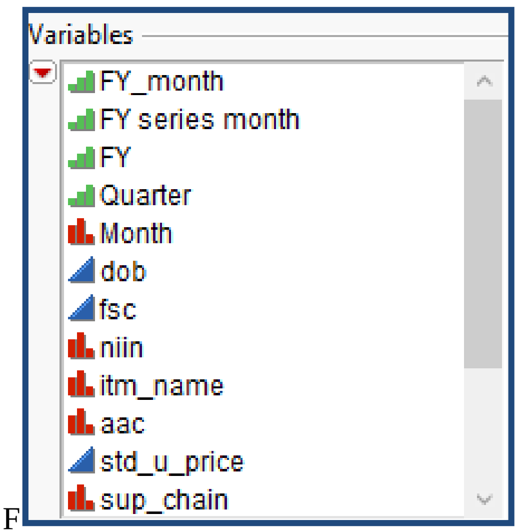


Table 9. Step 5, Part B

- **Step 6: Select X and Y Variables for the Graph**

Figure 23 contains a list of variables that can be used to build an X by Y graph. This list is part of the graph builder page, shown in Figure 24. Drag and drop variables to the center of the page as shown in Figure 24 to build a graph:

- In the x axis, drop the time-series variable, "FY_month"
- In the y axis, drop the variable "qty_req"



F

Figure 23. Step 6, Part B

- **Step 7: Select Graph Shape**

Figure 24 displays a graph builder options. Click on the icon at the top of the page to select the shape of the graph: Bar Graph. The demand model above displays monthly demand.

Below, Figure 25 also shows monthly demand data, but this time it is stacked by fiscal year. Figure 26 presents quarterly demand data by fiscal year. These graphs were produced using graph builder using the same steps described above in steps 1 to 7.

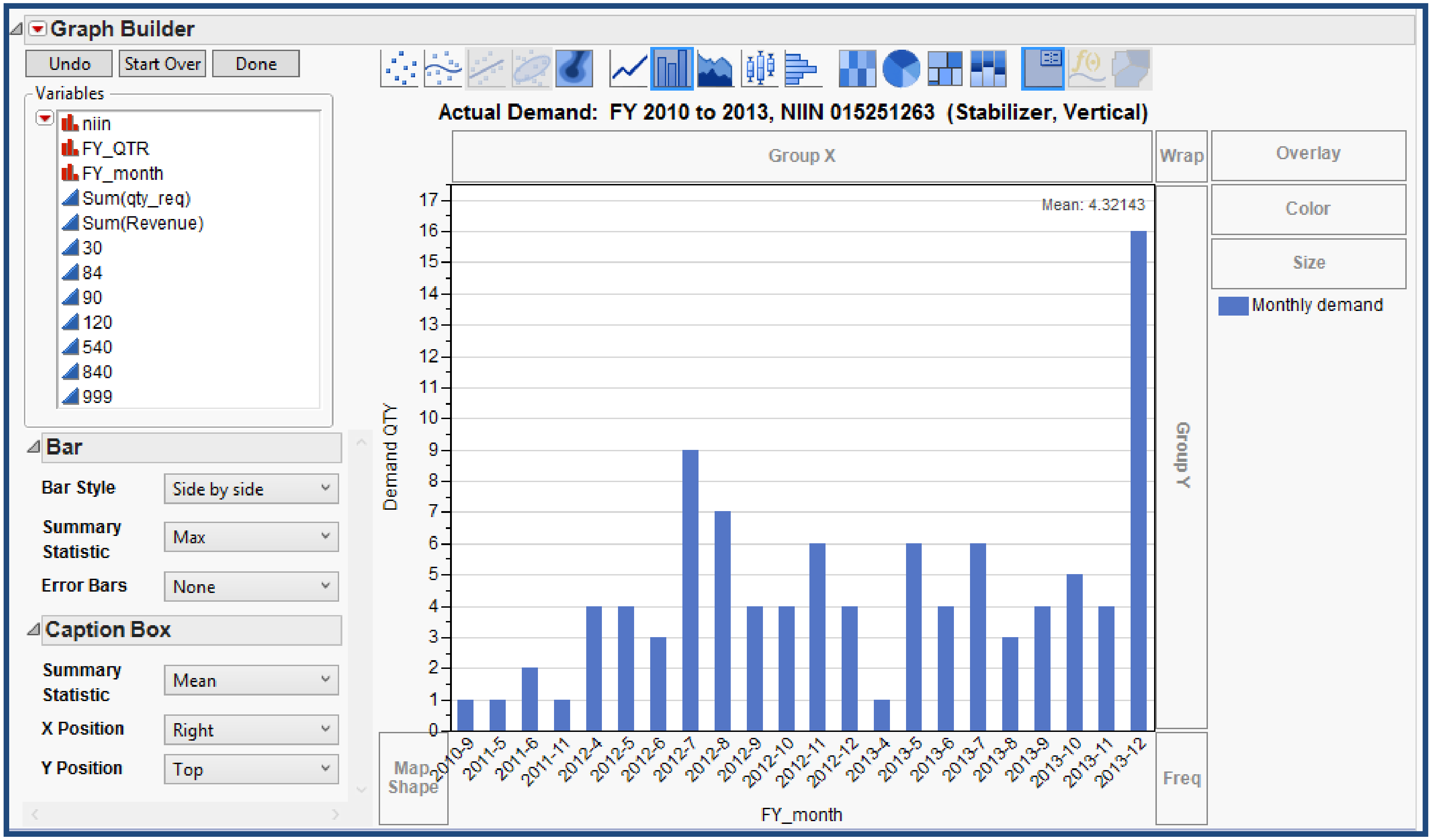


Figure 24. Step 7, Part B

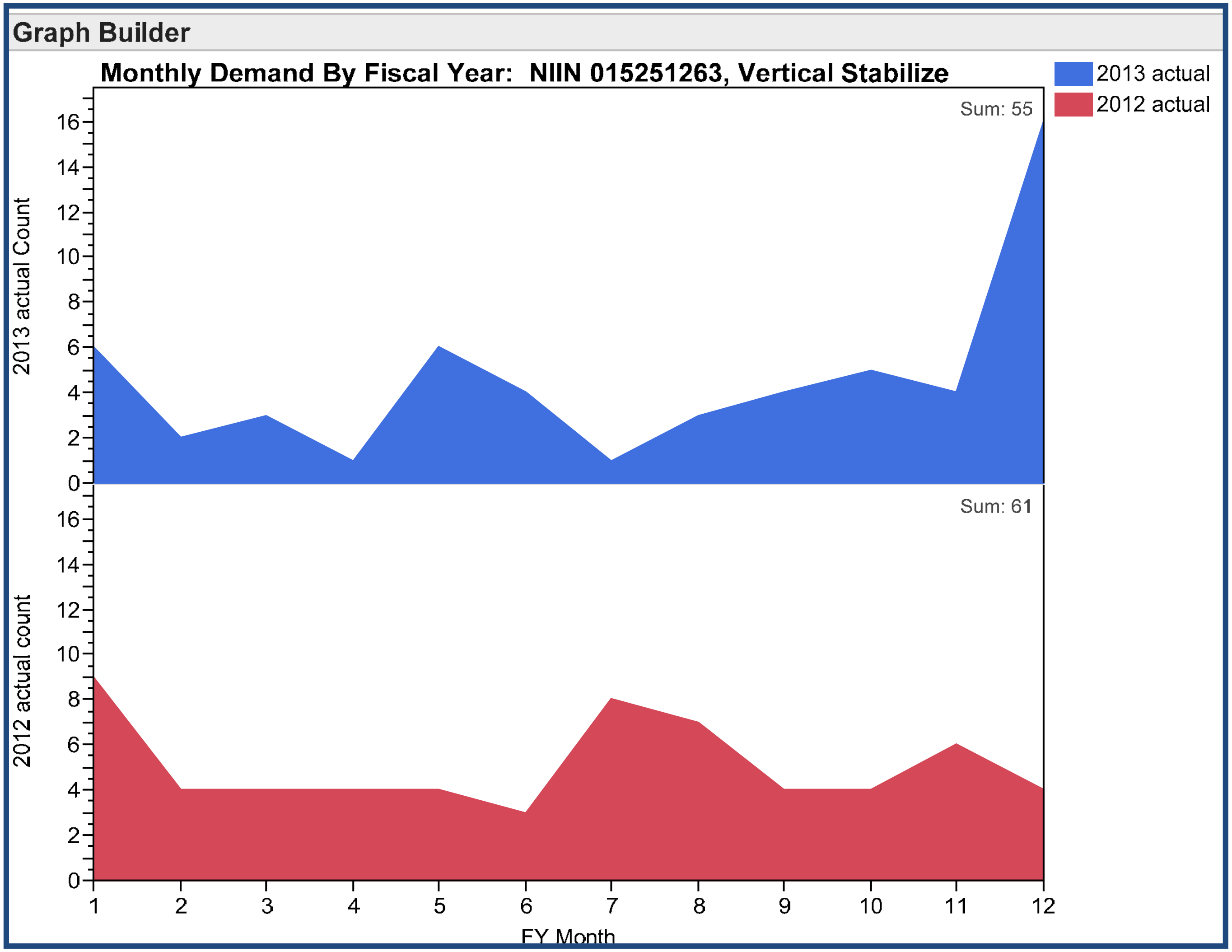


Figure 25. Monthly Demand by Fiscal Year

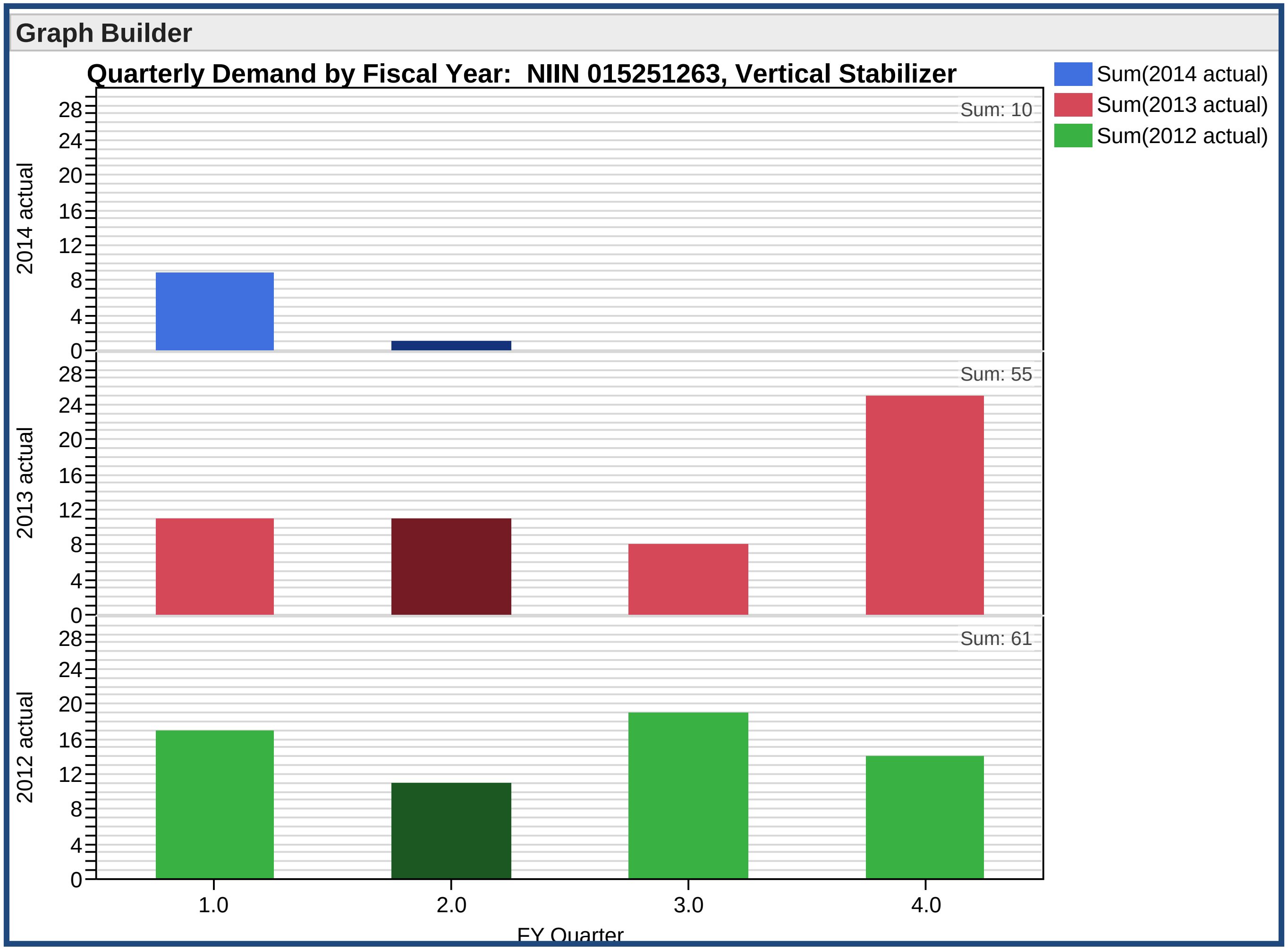


Figure 26. Quarterly Demand by Fiscal Year

G. LEAD-TIME DEMAND (LTD) FORECAST: THE RIGHT INPUT FOR INVENTORY MANAGEMENT POLICY

This research paper advocates for thinking about inventory levels in terms of lead time demand (replenishment cycle demand). Granted, it is often helpful to visualize and subsequently to present demand information to stakeholders within the organization in blocks of days, weeks, months, or years. However, representing demand in the intervals of time listed above does not necessarily provide the most useful information to be used in reordering stock, in accordance with an inventory management policy. A much more practical way to think of and visually present demand information is as a snapshot of lead-time demand (LTD), which describes product demand during the replenishment period, or reorder cycle. In other words, LTD information tells a forecaster (or inventory manager) the inventory quantity that is needed during the time between stock replenishments. The safety stock is the insurance or stock quantity maintained on hand to supplement LTD stock quantity in order to support a target service level between replenishment cycles.

Assessing the lead-time demand can be difficult, especially because demand for a product is not static, often random, sporadic, growing or in decline. The Demand Quantity for NIIN 015251263 (the stock item which generated the greatest revenue in the aviation supply chain during FY2013) was not constant across fiscal years from FY2010 to FY2013. Moreover, the lead time has changed significantly a number of times from FY2010 to FY2013. Historical data must be analyzed and trade-offs must often be made to determine what demand data to exclude (outliers) and which time segment to use, in order to represent the entire lead time period, in the case of extended lead time. For example, this forecast has a 32-month lead time for replenishment, but both the lead time and the demand varies across fiscal years. To simplify this problem for our forecast models, we used the current fiscal year's lead time (FY 2014), provided by DLA (not shown in Table 10). The total lead time is computed by adding two elements that added together become total lead time:

- FY2014 Admin Lead Time (ALT): 120 days

- FY2014 <u>Procurement Lead Time</u> (PLT): 840 days
- Total Lead Time: 960 days, or ~32 months

[Note: The shifting Admin and Procurement Lead Times observed in the table below represent an opportunity for the DLA to focus on negotiating significantly decreased lead times, which could result in both lower safety stock and improved use of cash flows, such as buying adequate amounts of more (different) critical stock equal to their target service level.]

Monthly Demand, Admin Lead Time (ALT) and Procurement Lead Time (PLT)

								Demand QTY	Revenue	alt				plt		
FY	Quarter	FY_MO	FY_MO Series	Calendar Month	niin	itm_name	std_u_price	Sum	Sum	30	84	90	120	540	840	999
2010	1	2010_3	3	12	015251263	STABILIZER,VERTICAL	$644,655.54	1	$644,655.54	0	0	1	0	0	0	1
2011	2	2011_5	5	2	015251263	STABILIZER,VERTICAL	$833,496.88	1	$833,496.88	1	0	0	0	1	0	0
		2011_6	6	3	015251263	STABILIZER,VERTICAL	$833,496.88	2	$1,666,993.76	2	0	0	0	2	0	0
	4	2011_11	11	8	015251263	STABILIZER,VERTICAL	$814,849.15	1	$814,849.15	1	0	0	0	0	1	0
2012	1	2012_1	1	10	015251263	STABILIZER,VERTICAL	$814,849.15	9	$7,333,642.35	5	0	0	0	0	5	0
		2012_2	2	11	015251263	STABILIZER,VERTICAL	$814,849.15	4	$3,259,396.60	2	0	0	0	0	2	0
		2012_3	3	12	015251263	STABILIZER,VERTICAL	$814,849.15	4	$3,259,396.60	3	0	0	0	0	3	0
	2	2012_4	4	1	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	1	0	0	0	0	1	0
		2012_5	5	2	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	2	0	0	0	0	2	0
		2012_6	6	3	015251263	STABILIZER,VERTICAL	$786,329.43	3	$2,358,988.29	2	0	0	0	0	2	0
	3	2012_7	7	4	015251263	STABILIZER,VERTICAL	$786,329.43	8	$6,290,635.44	5	0	0	0	0	5	0
		2012_8	8	5	015251263	STABILIZER,VERTICAL	$786,329.43	7	$5,504,306.01	3	0	0	0	0	3	0
		2012_9	9	6	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	2	0	0	0	0	2	0
	4	2012_10	10	7	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	0	0	3	0	3	0
		2012_11	11	8	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	0	0	3	0	3	0
		2012_12	12	9	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	0	0	3	0	3	0
2013	1	2013_1	1	10	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	3	0	0	0	3	0
		2013_2	2	11	015251263	STABILIZER,VERTICAL	$749,864.65	2	$1,499,729.30	0	1	0	0	0	1	0
		2013_3	3	12	015251263	STABILIZER,VERTICAL	$749,864.65	3	$2,249,593.95	0	2	0	0	0	2	0
	2	2013_4	4	1	015251263	STABILIZER,VERTICAL	$749,864.65	1	$749,864.65	0	1	0	0	0	1	0
		2013_5	5	2	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	3	0	0	0	3	0
		2013_6	6	3	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	2	0	0	0	2	0
	3	2013_7	7	4	015251263	STABILIZER,VERTICAL	$749,864.65	1	$749,864.65	0	1	0	0	0	1	0
		2013_8	8	5	015251263	STABILIZER,VERTICAL	$749,864.65	3	$2,249,593.95	0	2	0	0	0	2	0
		2013_9	9	6	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	2	0	0	0	2	0
	4	2013_10	10	7	015251263	STABILIZER,VERTICAL	$782,639.44	5	$3,913,197.20	0	2	0	0	0	2	0
		2013_11	11	8	015251263	STABILIZER,VERTICAL	$782,639.44	4	$3,130,557.76	0	2	0	0	0	2	0
		2013_12	12	9	015251263	STABILIZER,VERTICAL	$782,639.44	16	$12,522,231.04	0	7	0	0	0	7	0

4 rows have been excluded.

Table 10. Monthly Demand, Admin Lead Time and Procurement Lead Time

- **Lead-Time Demand Analysis and Forecast**

The lead time (LT) for NIIN 015251263 (Vertical Stabilizer) is 960 days, or about 32 months.

Once the lead time has been calculated, the next step is to statistically analyze lead time demand. Continuing with the example used above, NIIN 015251263, FY2010 to FY2013 demand data was analyzed, and it was determined that the FY2013 demand data should be used as the time segment for forecasting the replenishment cycle's lead time demand (32 months). Table 10 above displays the monthly demand for NIIN 015251263 during FY 2011 to FY 2014. Total demand volume was relatively insignificant during the first two years of this observation period: one unit of demand in FY 2010 and three units in FY 2011. Of the four years observed, the first two years were ruled out as insignificant for predicting future demand. Demand increased significantly during FY2012 to 2013. Because FY2013 demand is most recent, we assumed it was the most relevant information; therefore FY2013 data was used as the time segment for predicting future demand. Additionally the outlier demand value for September 2013 (2013_12) was not used for calculating parameters for our demand forecast simulation. Generally, we consider a monthly demand hit an outlier value when it is higher than 2 standard deviations from the mean. The result of the statistical analysis showed that the Poisson distribution had the best goodness of fit with the historical demand, given the parameter, rate equals 2.55 [Refer to Appendix A for more details.].

The next step is to use the Poisson distribution and parameter, rate = 2.55, in the Crystal Ball Monte Carlo simulation. Note that Inventory Policy Values (reorder point and safety stock) are obtained from a Monte Carlo forecast simulation. Crystal Ball computes forecast simulations in the following manner:

- The forecast value for one month (x1) is the mean value of 100,000 trials where one independent trial is denoted by y variable.
- x1 = sum (y1 + y2.... + y100,000)/100,000.

- Therefore, the expected value of a six-month forecast = sum of (x1 + x2 + x3 + x4 + x5 + x6); where variable x denotes the month and the average demand quantity. For example, the average demand quantity for October 2013 equals 2.5 units. Another example, over a period of six months, the average demand quantity equals 15 units (computed by 2.5 average monthly demand times 6 months).

Figure 27 illustrates a Monte Carlo forecast simulation generated using Crystal Ball software. The standard for this research is to run a simulation with 100,000 trials to produce a demand forecast simulation. As seen below, the "Poisson Distribution" with parameter, rate = 2.5, produced a forecast simulation for 32 months lead time demand. The most likely outcome (mean) is the forecast: ~82 units. The certainty block is used to obtain the inventory quantity for a target service level. Given below is a target service level of 95% and the matching quantity is 97 units.

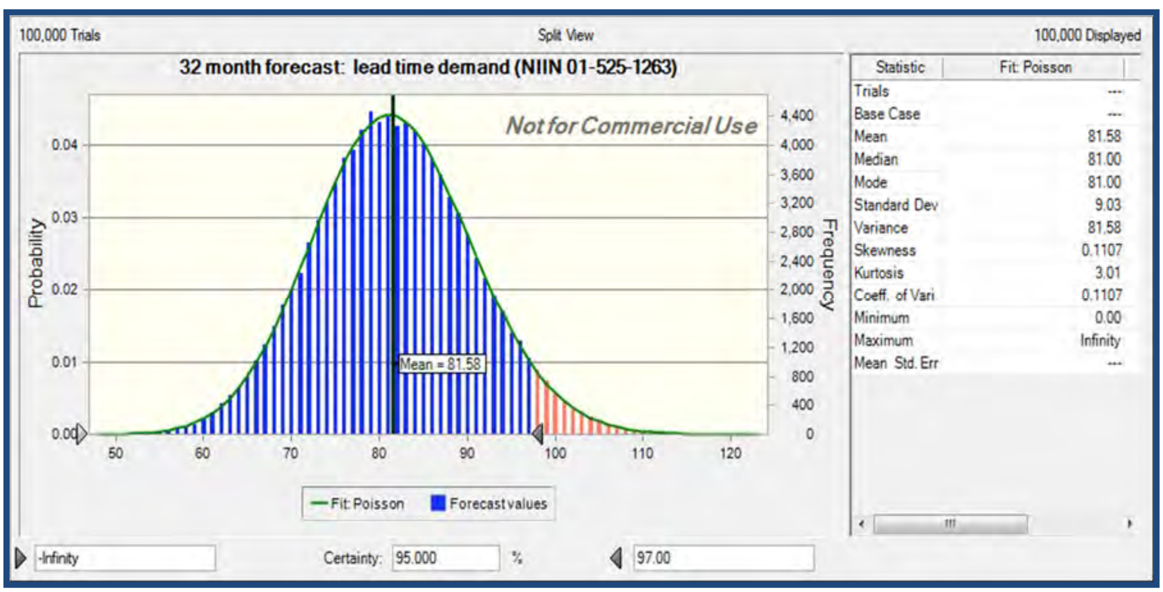


Figure 27. Crystal Ball-Generated Demand Forecast Simulation

The expected, or average, lead-time demand (32 months) for NIIN 015251263, vertical stabilizer, is 82 units. For a 95% service level demand quantity is increased to 97 units. Therefore, to interpret the results of this Monte Carlo simulation, one should set the

reorder point at 97 units, which already includes a safety stock of 15 units (computed by subtracting the 95% service level quantity minus the forecast quantity, or 97 – 82 = 15).

- **Reorder Point (ROP)**

The actual reordering point (168 units) was provided by the DLA, as seen in Table 10.

Evolving Inventory Policy: Narrowing the gap beween the model and the real world			
	Actual DLA QTY	1st forecast	**2nd forecast**
Effective date:	FY 14	Oct-13	**Apr-14**
Forecast		82	**53**
Safety Stock:	32	15	**12**
Reorder Point:	168	97	**65**
The market for this product is non-static, characterized by shifting conditions and uncertainty.			
The Apr-14 forecast used 6 months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.			
FY-14 unit price	Delta	cost savings	cost increase
$782,639	103	$80,611,862	

Table 11. ROP versus Forecast Comparison

Since this NIIN is a class-A stock item, it should be managed using a continuous-review inventory policy. Further details about setting an inventory policy are provided in Appendix 1 for this NIIN.

H. CONDITIONAL VALUE AT RISK (CVAR)

Next, we used the Monte Carlo simulation to measure the risk of running out of stock. Using Crystal Ball, a conditional value at risk (CVAR) is produced by separating the right tail, or remaining 5% probability for a 95% service level (95% + 5% = 100%). A CVAR is the expected quantity that will not be filled from stock, given that the quantity demanded exceeds the inventory on hand.

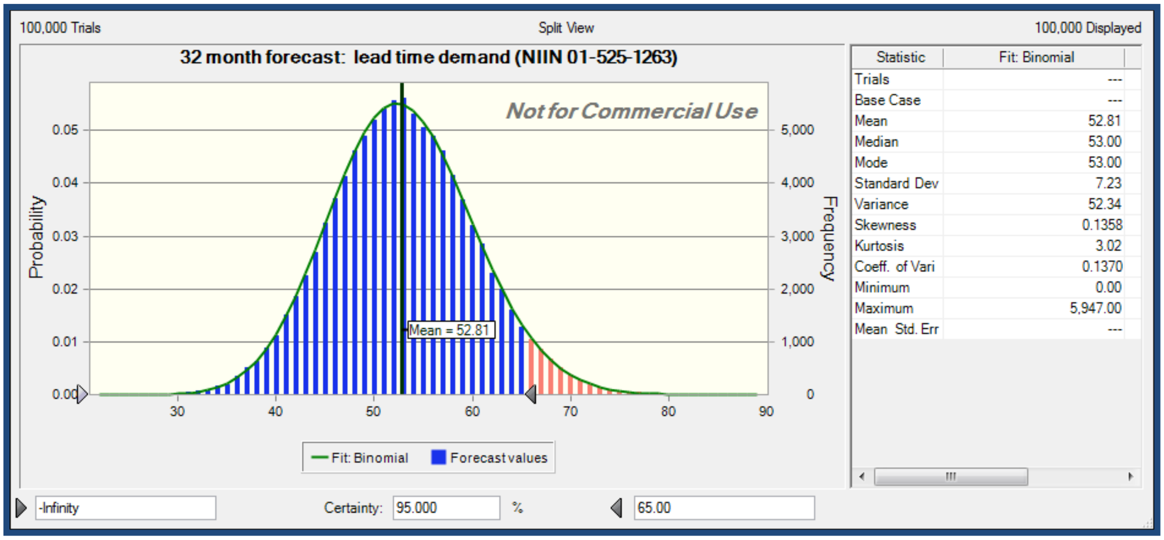


Figure 28. Crystal Ball-Generated Demand Forecast

This step requires one to assess the risk of stocking out due to demand variability. The 95% service level is shaded in blue in Figure 28 and the value of this area under the demand curve is 65 units. The remaining 5% is the conditional value at risk (right tail of the distribution curve). The second graph below, Figure 29, represents the range of outcomes for the conditional value at risk and provides an answer to the question, "if stock runs out, how bad can things get?" The answer is obtained by subtracting the maximum value of the forecast minus the 95% service level quantity, which equals 24 units maximum shortage (89 - 65) = 24). Most importantly, the graph below answers a more astute question, "if stock runs out, what is the expected shortage quantity?" The answer is found by subtracting the mean value of this right tail minus the target service level quantity: 69 units - 65 units = 4 units as expected shortage quantity.

“

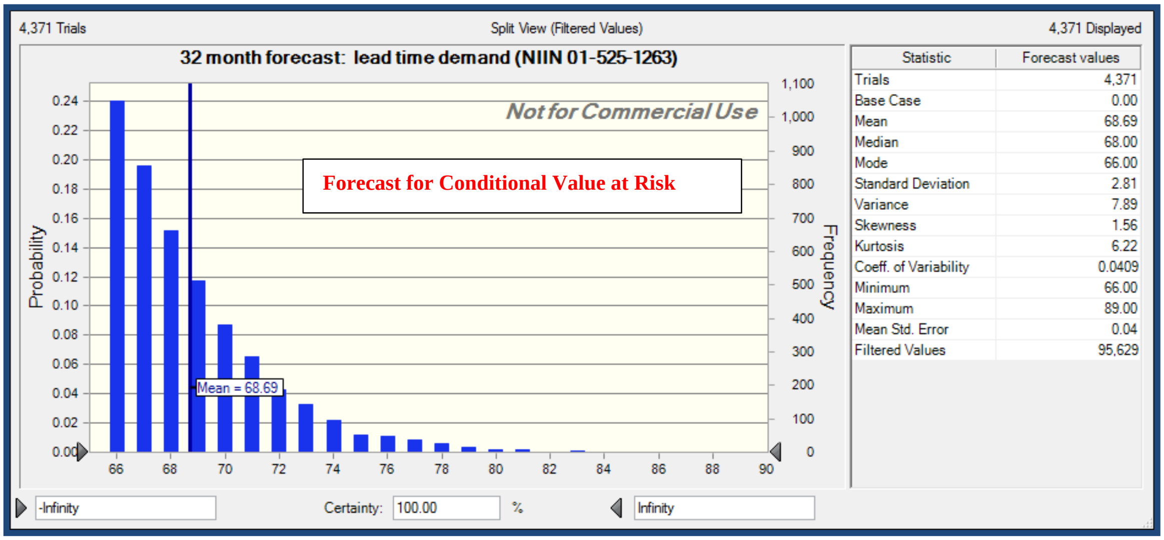


Figure 29. Measure of Stock-out Risk (Conditional Value at Risk)

I. INVENTORY POLICY FORMULATION

For the purpose of this research the DLA goal is a 95% service level for customer orders. Put another way, the goal is to fulfill an average of 95 of every 100 orders. Therefore, the inventory manager must formulate a rough inventory policy and make adjustment which best fit the organization’s intention. Table 12 depicts the summary conclusions from the Monte Carlo simulations above:

The average lead time demand forecast (50% probability)	53 units (lead time = 32 months)
A 95% service level quantity equals	65 units of inventory
Conditional risk: If demand exceeds stock on hand during the replenishment cycle, the expected shortage is	4 units (see forecast right tail distribution: 69 - 65 = 4)
How bad can things get if there is a stock out? The maximum shortage forecasted is	24 units (89 – 65 = 24).

Table 12. Monte Carlo Simulation Highlights

Other highlights for the inventory manager's consideration are as follows:

- Keep in mind that increasing either or both the safety stock or cycle stock increases the material cost and inventory holding costs, and this stock becomes dead weight unless it is sold.
- One thing is almost certain: The lead time demand forecast of 53 units is bound to be inaccurate due to fluctuating demand. However, the forecast range should be highly accurate. Even though demand for this stock item is dynamic and shifting over time, the actual demand quantity over 32 months could fall at any point along the demand probability distribution curve.
- The DLA should produce demand forecasts and risk analysis for this NIIN at least on a quarterly basis and adjust the inventory policy (Reorder Point and Safety Stock levels) as required. This implies integrated planning is necessary with the contracting officer and item manager for negotiating the right procurement contract with the supplier(s).

{*Note: The statistical analysis, forecasting, and risk analysis conducted in this chapter are provided solely to explain and provide visual representation of the process followed in this research for understanding demand volume, demand pattern, probability distribution and stock-out risk. Forecasts and frequently forecast updates were produced for 50 NIINs which can be reviewed in the appendices section. There was a learning curve in producing these forecasts. The reader is recommended to read appendices 30 to 50 for the best explanations about the process described above.}*

In closing, this chapter described the statistical analysis and forecasting simulation techniques. The following chapter presents a summary of findings from this research project.

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IV. ANALYSIS OF LEAD TIME DEMAND AND FORECAST SIMULATIONS

This chapter introduces statistical analysis of demand and the resulting demand forecasts for DLA Aviation Supply Chain inventory. The goal is to inform the reader of the process followed in each addendum as well as to present summary results of this research project. The detailed work is found in appendices 1 to 50; however, due to the large document size, we include five appendices only containing individual stock item analysis and forecasts. The complete list of appendices is available upon request via the following link: www.acquisitionresearch.net. Summary of discussion is as follows:

- Organizing historical product demand data
- Statistical analysis of product demand
- Lead time demand forecast: an input for inventory management policy
- Inventory policy formulation
- Conditional value at risk analysis
- Forecast results versus FY14 DLA inventory level
- Material Inventory Cost and Holding Cost Impacts by Class A NIIN

A. ORGANIZING HISTORICAL PRODUCT DEMAND DATA

Chapter III informs that the DLA provided 4.5 years of product demand data, or over 5 million requisition records from FY 2010 to FY 2014.

We used JMP PRO 10 software to consolidate data into an ABC classification method (Chapter III) to identify stock items (NIINs) that had the highest impact on revenue in FY 2013. Demand data from FY 2013 was organized in descending order listing by NIIN with the highest revenue. This list totaled 55,000 NIINs. Class A NIINs were the top 10 percent (or top 5,500 NIINs), which made up almost 80% of FY 2013 revenue value. Figure 30 is a graphical depiction of Class A NIINs. For a complete list of Class A NIINs, please refer to Exhibit A found in following link: www.acquisitionresearch.net, which is the focus of this research.

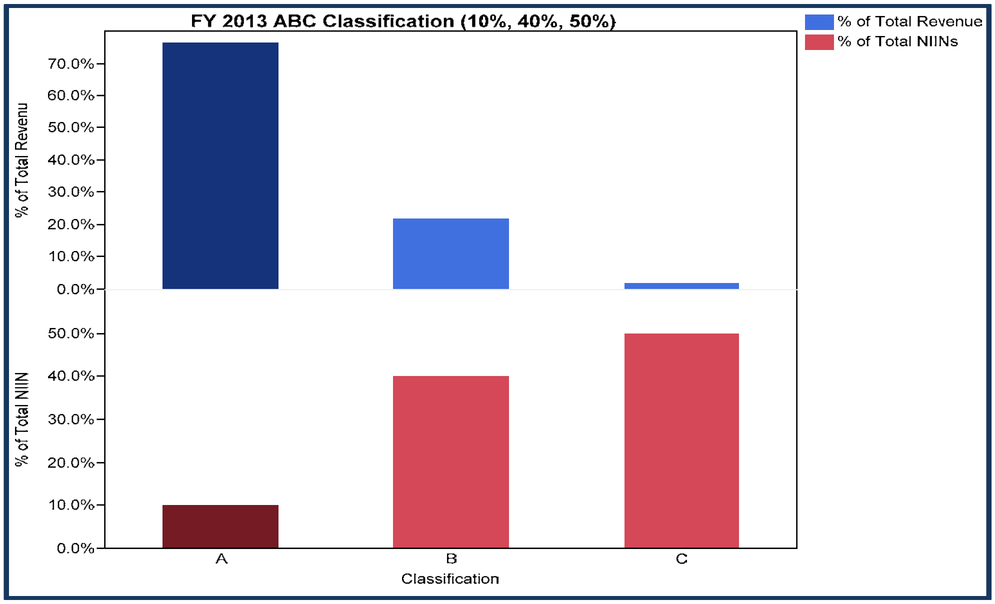


Figure 30. FY13 ABC Classification

As shown in Figure 31, we noted that most of the Class A NIINs that were present in FY 2010 (base year) did survive transitioning from FY 2011 to FY13. The same was true for the Class A NIINs from FY 2011 (base year) to FY 2012 and Class A NIINs from FY 2012 (base year) to FY 2013. The implication of this finding is that a Class A list will not be the same from year to year, but the effort of producing such a list is worthwhile as a guide for allocating resources.

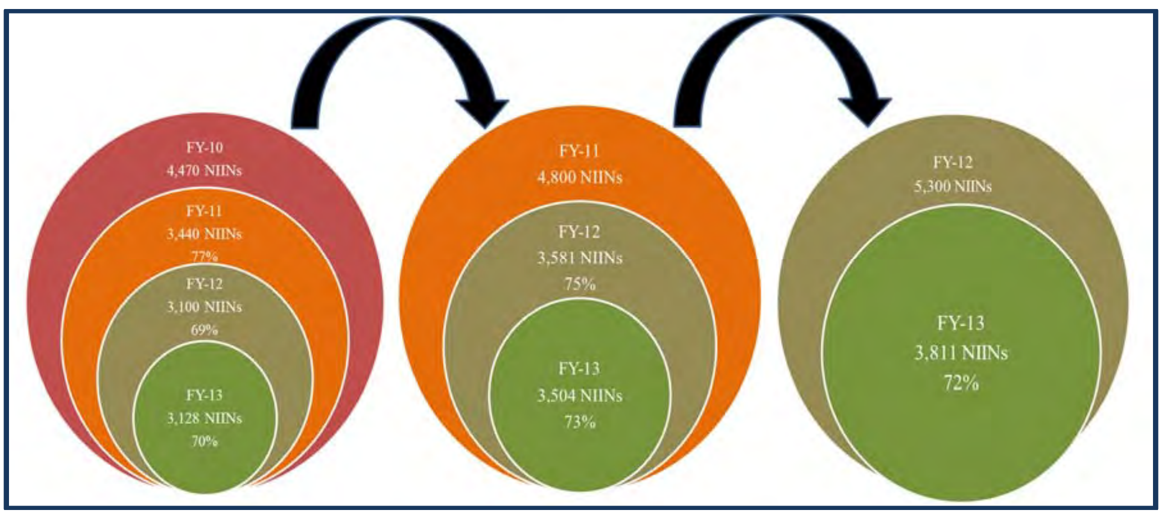


Figure 31. ABC Classification NIIN Survivability

B. STATISTICAL ANALYSIS OF PRODUCT DEMAND

The foundation of most forecasting processes begins with getting a clear understanding of historical data to account for trend using advanced statistical analysis software.

- **Project Appendices**

Using JMP PRO 10 software outputs, the appendices detail product demand statistical analysis and visual representation of demand patterns and demand probability distribution by individual NIIN.

- **Visual Representation of Demand Data: Volume and Variability**

The appendices contain visual representation of patterns for product demand volume and variability across time, using bivariate (X by Y) analysis graphs as shown in Figure 32.

- **Demand Patterns**

Visual representation of demand data in the appendices helps to identify general demand patterns across fiscal years, such as increasing, decreasing, random, cyclical and stable demand patterns. Some of these patterns are shown in Figure 33.

Visual representation of actual demand data also helps to identify a time segment which appears reasonable as a representative time segment demand for modeling future demand, such as during a replenishment cycle. For example, demand data from the selected time segment (FY13 in this case) is used to draft a demand data histogram as shown in Figure 34, which includes goodness of fit tests for probability distributions of demand (see Chapter II for probability distribution description).

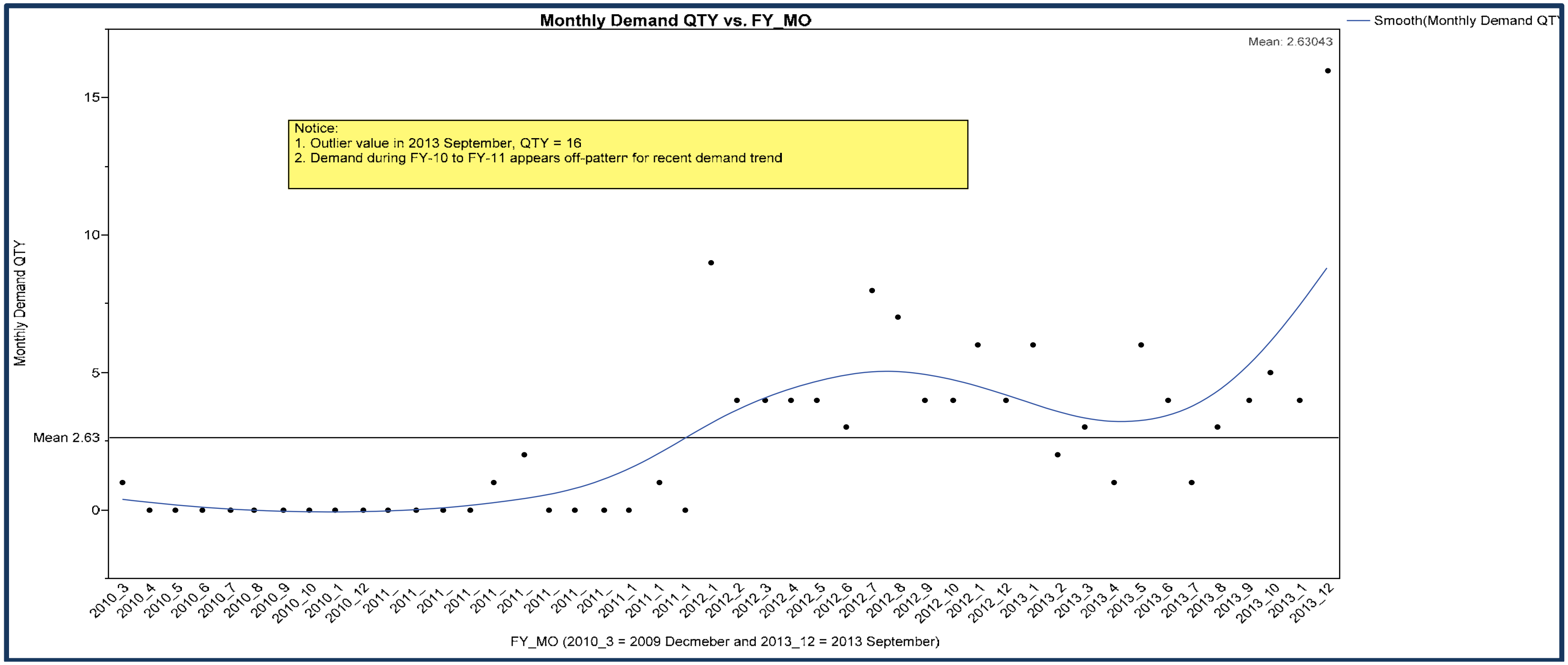


Figure 32. Monthly Demands QTY versus FY10 to FY13

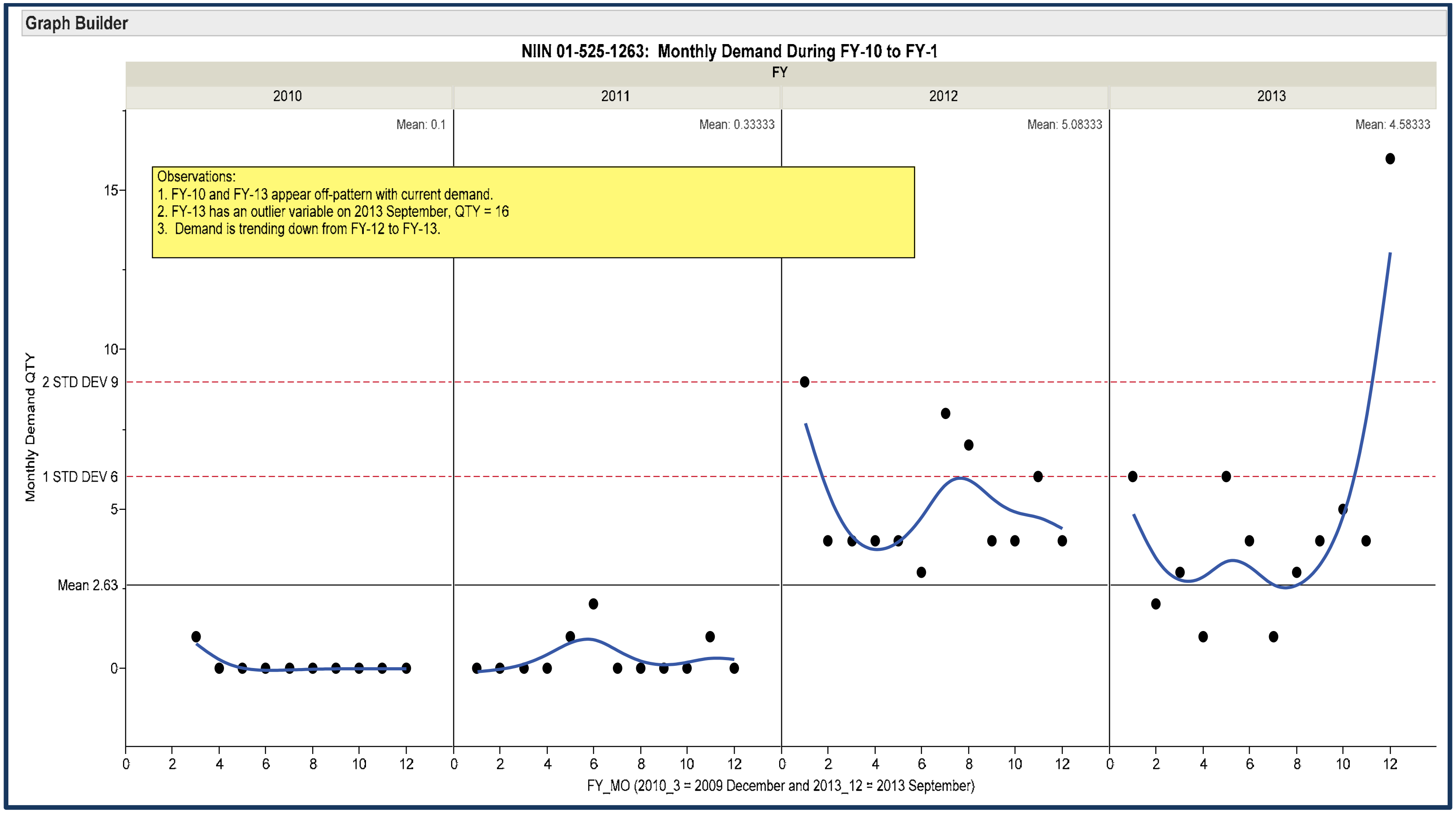
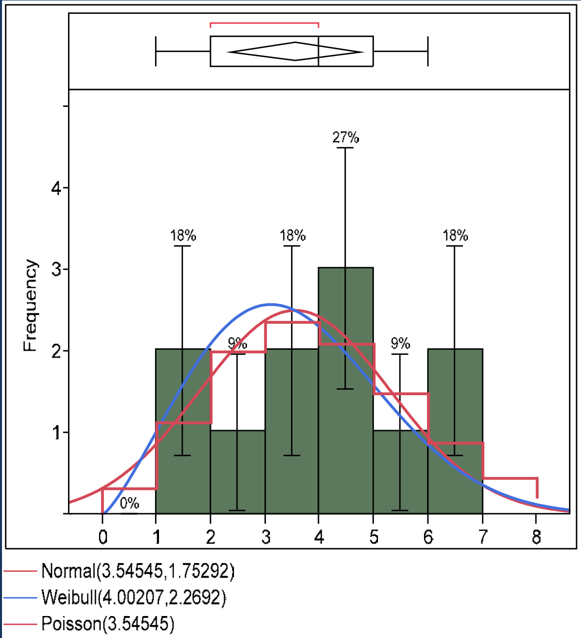


Figure 33. Monthly Demand During FY10 to FY13 Time segments



Quantiles: FY-13 Monthly Demand, NIIN 01-525-1263		
100.0%	maximum	6
99.5%		6
97.5%		6
90.0%		6
75.0%	quartile	5
50.0%	median	4
25.0%	quartile	2
10.0%		1
2.5%		1
0.5%		1
0.0%	minimum	1

Summary Statistics	
Mean	3.5454545
Std Dev	1.7529196
Std Err Mean	0.5285252
Upper 95% Mean	4.723082
Lower 95% Mean	2.3678271
N	11
Variance	3.0727273
Skewness	-0.092266
Kurtosis	-0.923054
Median	4
Mode	4
Range	5
Interquartile Range	3

Figure 34. Historical Demand Data Histogram

- **Histogram: Probability distributions**

The JMP analysis section in each appendix includes histograms representing demand distribution analysis with goodness of fit test scores, usually for multiple probability distributions (such as the normal distribution, Poisson distribution, etc.). Using this analysis, where the distribution with the highest p-value is used, we formulate a hypothesis for demand patterns and probability distributions of each NIIN. As supported in Figure 35, an example of a hypothesis might read, “based on the goodness of fit test for the fitted distribution, [during the given time segment], our hypothesis is demand data follows a Poisson distribution, with parameter scale = 3.5.” This stated hypothesis in each appendix is the basis for running a specific demand forecast simulation using Crystal Ball Monte Carlo simulations.

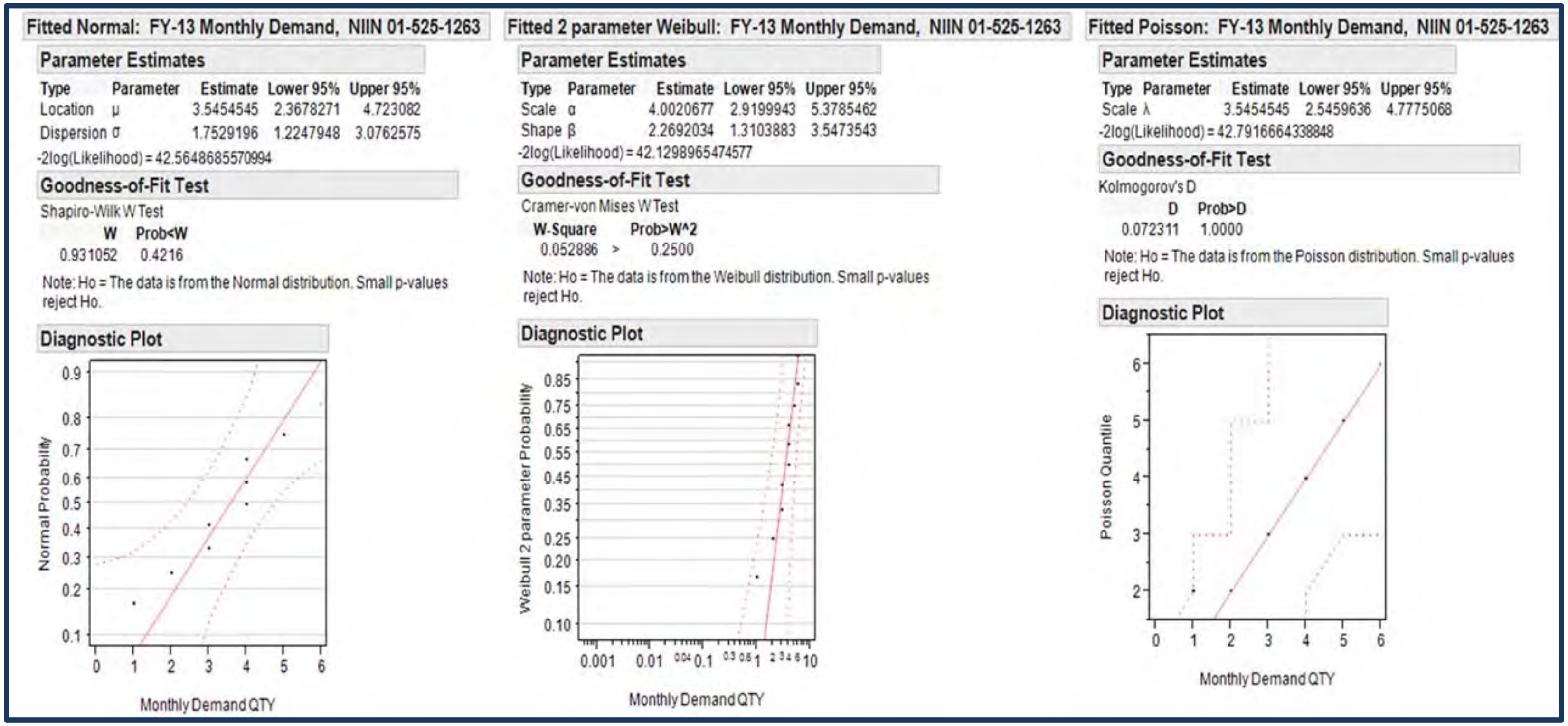


Figure 35. Fitted Distribution

C. LEAD-TIME-DEMAND FORECAST: AN INPUT FOR INVENTORY-MANAGEMENT POLICY

Today’s lean economic conditions and demand uncertainty make it more challenging to make adequate investments in inventory. By taking into account both the average demand quantity and the lead time variability during the replenishment cycle (lead time) one can at least plan on adequate inventory quantity. Therefore, for a target service level, an effective inventory policy starts with a lead-time-demand forecast that mitigates stock-out risk with adequate safety stock quantity.

- **Lead-Time Demand**

Lead-time demand (LTD) is computed as follows:

Admin Lead Time + procurement Lead Time = Total Lead Time

LTD = Average Monthly Demand x Total Lead Time

Lead-time demand is the expected demand during replenishment cycles. The word ‘expected’ implies that this is the average demand during the lead time. Each appendix contains a set of forecasts including lead-time demand, 2014 fiscal year demand and a six month demand forecast.

- **Forecast**

A Monte Carlo simulation provides a range of forecast outcomes with a given probability associated with each outcome. The most likely outcome (the mean) is the demand forecast; or, as shown in the Monte Carlo simulation in Figure 36, the forecast is the mean value of ~53 units. Notice that the 95% certainty value is provided. The certainty value is the target service level quantity. Therefore, for a 95% target service level, the recommended inventory quantity is 65 units.

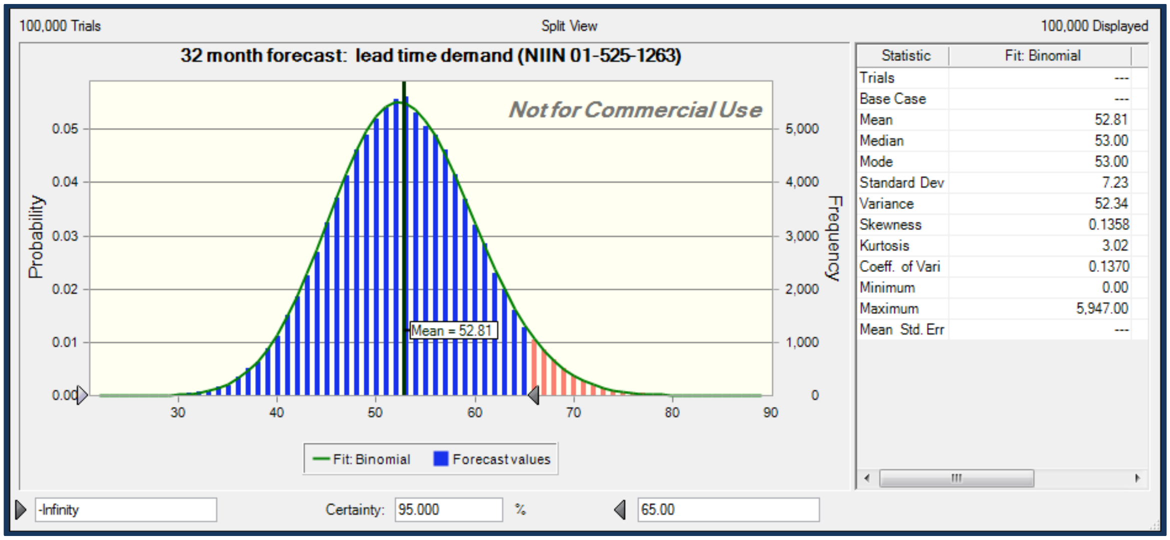


Figure 36. Monte Carlo Simulation

- **Recommended Forecasting Techniques by Demand Pattern**

The recommended forecasting technique involves using the selected probability distribution with the best goodness of fit score. This probability distribution along with the parameter(s) identified in the statistical analysis section found in each appendix is inputted into a Crystal Ball forecast simulation model. The result is a set of demand forecast simulations or Monte Carlo simulations such as the one shown above.

D. INVENTORY POLICY FORMULATION

- **95% fill rate = Lead Time Demand + Safety Stock = Reorder Point**

The DLA goal is to provide a 95% service level to its customers. That is, the agency's goal is to be able to fill 95% of all customer demand by NIIN from inventory on hand. The Monte Carlo simulation technique makes it easy to quickly determine the 95% service level by selecting the 95% certainty as an output display requirement. Figure 37 illustrates this concept.

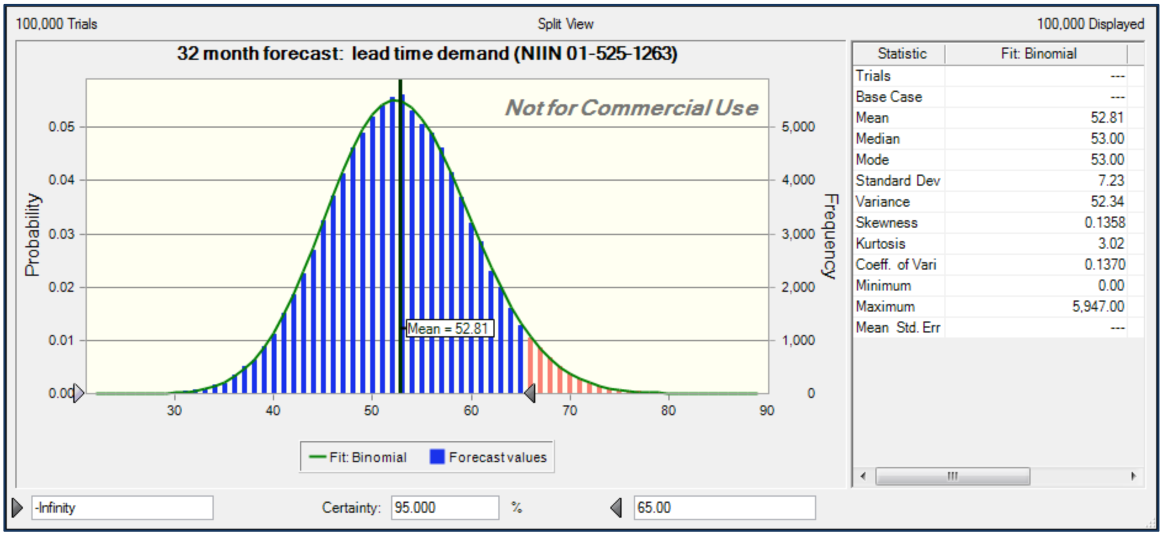


Figure 37. Monte Carlo Simulation 95 percent Service Level

The stock reorder point is the 95% service level quantity; therefore, whenever stock is reduced to this inventory level, a reorder should be sent to the supplier for the lead-time demand quantity or if preferred by the organization, the economic order quantity or a lot size quantity. As Figure 38 shows, the safety stock (SS) is the difference between the reorder point (ROP) quantity less the lead time demand quantity (demand forecast quantity). This can be easily computed from the Monte Carlo simulation.

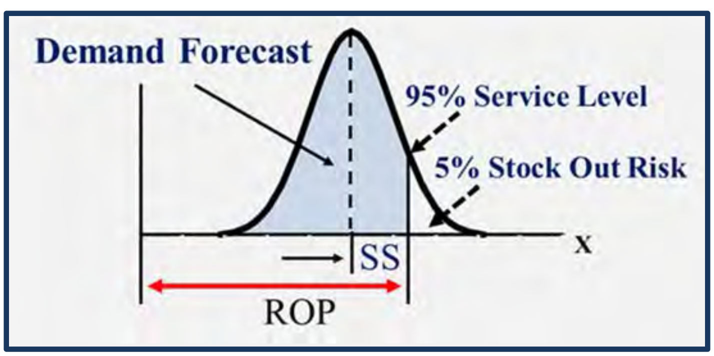


Figure 38. ROP and Safety Stock

The Monte Carlo simulation contains the information necessary to formulate inventory policy recommendations from lead time demand forecast, safety stock and reorder point, as shown in Figure 39.

Inventory Level for a Combined Variable Demand and Constant Lead Time:

Reorder Point = (Lead Time x demand) + Standard Deviation of Demand During Lead Time

Reorder Point = Lead Time Demand + Safety Stock

Reorder Point = 95% Service Level

Figure 39. Inventory Level Formula

- **Actual FY14 DLA Inventory Levels versus Our Forecast Models**

Both the actual inventory quantities and the actual demand for FY14 (October 2013 to March 2014) were provided to us by DLA. However, these quantities were not used during the statistical analysis phase or the forecasting phase. Therefore, actual demand data for FY14 was used after the forecast was completed in order to gauge the performance of our forecast models. We assumed that a forecast for the incoming fiscal year was run in October. If that forecast was highly accurate we did not run a second forecast. Conversely, if the forecast could be much improved, then a second forecast was run, and we assumed this was the mid-year forecast update run in April. This process created a tracking signal that enabled calculated inventory level adjustment (see Table 13).

Evolving Inventory Policy: Narrowing the gap beween the model and the real world			
	Actual DLA QTY	1st forecast	2nd forecast
Effective date:	FY 14	Oct-13	Apr-14
Forecast		82	53
Safety Stock:	32	15	12
Reorder Point:	168	97	65
The market for this product is non-static, characterized by shifting conditions and uncertainty.			
The Apr-14 forecast used 6 months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.			
FY-14 unit price	Delta	cost savings	cost increase
$782,639	103	$80,611,862	

Table 13. ROP versus Forecast Comparison

E. CONDITIONAL VALUE AT RISK ANALYSIS

This section in each addendum provides the summary of the research finding for a NIIN. The demand forecast, safety stock and reorder point are provided. Also, the conditional value at risk is discussed, which is the expected value of demand during a stock out. Figure 40 below shows the conditional value at risk, which is the expected shortage in the event of a stock out, computed as follow:

Expected stock out quantity = mean - target service level quantity = 69 – 65 = 4 units short.

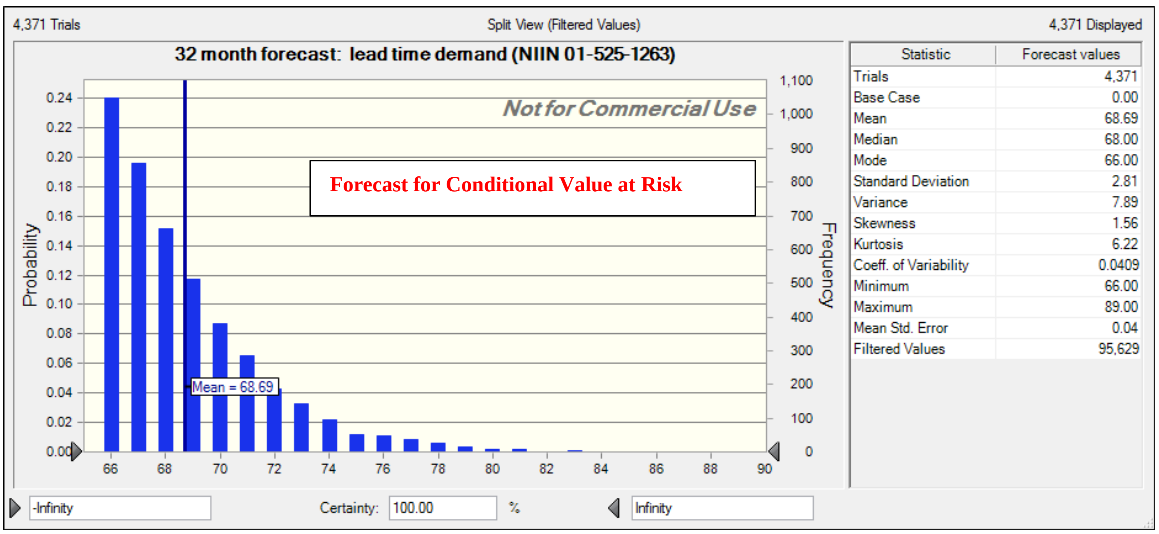


Figure 40. Conditional Value at Risk

The Monte Carlo simulation above provides a range of values for a forecasted stock out (or values above the 95% service level) to answer the question, "how bad can things get during a stock out?" As shown in the Monte Carlo simulation, the maximum forecasted demand is 89 units. Therefore, compute the forecast maximum stock shortage as follow:

How bad can things get = Maximum forecast value – target service level quantity

= 89 – 65 = 24 units short maximum

F. FORECAST RESULTS VERSUS FY14 DLA INVENTORY LEVEL

This section displays summary results of our forecast analysis of the top 50 Class A NIINs and compares forecast values versus DLA's actual inventory for FY 14.

- **Material Inventory Cost**

Table 14 lists Class A items with side-by-side forecast results versus the actual FY14 DLA inventory. The forecast values (replenishment cycle) lead time demand, safety stock and reorder point are identified. Additionally, a <u>cost</u> column presents the theoretical impact of implementing the forecast results by resetting inventory levels as either an increase or a decrease in material costs. Lastly, the far right column lists the <u>cumulative material cost</u> effect of implementing forecast results. Material inventory cost was computed as follow:

Material Cost = *Unit Cost x Quantity*

DLA = \$782,639.44 *x* 168 = \$131,483,425.90

Forecast = \$782,639.44 *x* 65 = \$50,871,563.60

Material Cost Decrease = <u>\$80,611,862.30</u>

- **Holding Cost**

"Holding cost is a multiple of the average inventory size" (Ferrer, 2014, Class Handout). To simplify the problem, we make three assumptions. First, we describe average inventory as one half the reorder point listed for each unit in the table below. Second, the DLA provided 18% as the holding cost per unit. Third, unit selling price is used in lieu of unit cost. Therefore, holding cost is computed by multiplying 18% times the unit price, times one-half the reorder point. Table 15 provides the theoretical dollarized cumulative effect of implementing the forecast reorder point. Holding costs were computed as follow:

Total Holding Cost = (Unit Holding Cost) (Safety Stock + Cycle Stock/**2**)

Current = (18% * \$782,639.44) (**168 - 53** + **53**/**2**) = \$19,933,836.54

Proposed = (18% * \$782,639.44) (**65 - 53** + **53**/**2**) = \$5,423,691.32

Holding Cost Decrease = \$14,510,135.22

Note: Demand forecast simulations were completed for a total of fifty NIINs belonging to the FY2013 Class A stock category. The potential material cost reductions were:

<u>Potential Holding Cost Decrease = ~$60 million</u>

<u>Potential Material Cost Decrease = ~$300 million</u>

Rank	CLASS	Item Name	NIIN	Lead Time (ALT + PLT)	Lead Time Demand Forecast	Recommend Safety Stock	Actual DLA Safety Stock	95% service level forecast = Reorder Point	Actual DLA Reorder Point	Cost (Reduction) or increase	Cumulative Cost (Reduction) or increase
1	A	STABILIZER,VERTICAL	015251263	32 months	53	12	32	65	168	($80,611,862)	($80,611,862)
2	A	BLADE,TURBINE ROTOR	014634340	9 months	2,799	346	1,590	3,145	12,414	($43,081,570)	($123,693,433)
3	A	THERMOCOUPLE,CONTA(	015075310	12 months	17,086	1,498	1,915	18,584	22,127	($2,678,508)	($126,371,941)
4	A	FAIRING,AIRCRAFT	011707951	9 months	388	178	247	566	963	($92,414)	($126,464,354)
5	A	PARTS KIT,TURBINE E	015216584	12 months	182	10	4	192	267	($8,494,868)	($134,959,223)
6	A	NOZZLE SEGMENT,TURB	014683897	10 months	3,736	667	1,446	4,403	6,438	($5,708,969)	($140,668,191)
7	A	MODIFICATION KIT,EL	015536270	15 months	8	4	2	12	13	($1,230,484)	($141,898,675)
8	A	FLAMEHOLDER,AFTERBU	015526939	12 months	168	22	52	190	243	($2,235,592)	($144,134,268)
9	A	BLADE,TURBINE ROTOR	015122274	4 months	1,662	1,525	1,385	3,187	9,304	($5,945,112)	($150,079,380)
10	A	EJECTOR,JET	015404180	20 months	286	51	0	337	259	$3,695,971	($146,383,409)
11	A	MODIFICATION KIT,EL	015536292	16 months	3	4	1	7	5	$4,058,870	($142,324,540)
12	A	MODIFICATION KIT,EL	015536302	14 months	7	5	2	12	8	$6,472,477	($135,852,062)
13	A	PARTS KIT,TURBINE E	016053382	13 months	74	26	0	100	66	$3,011,382	($132,840,680)
14	A	MODIFICATION KIT,EL	015536300	18 months	2	3	1	5	2	$4,853,730	($127,986,950)
15	A	RESCUE UNIT,EMERGEN	014210084	11 months	10,865	3,265	74	14,130	11,020	$1,240,517	($126,746,433)
16	A	SEAT,AIRCRAFT	014943019	13 months	66	14	12	80	97	($659,260)	($127,405,693)
17	A	BEARING, PLAIN, ROD EN	014170133	16 months	1,858	70	273	1,928	1,753	$741,099	($126,664,595)
18	A	PARTS KIT,GAS TURBI	015522767	10 months	55	13	4	68	61	$161,340	($126,503,255)
19	A	BLADE,TURBINE ROTOR	011469445	12 months	5,113	1,176	454	6,289	5,451	$1,072,422	($125,430,833)
20	A	HEAD,ROTARY RUDDER	015152613	25 months	173	22	9	195	134	$4,323,915	($121,106,918)
21	A	BLADE,TURBINE ROTOR	012203928	14 months	29,546	5,856	0	35,402	13,933	$3,628,261	($117,478,657)
22	A	FLAMEHOLDER,AFTERBU	014503755	12 months	146	20	0	166	210	($21,564,090)	($139,042,747)
23	A	ILLUMINATOR,INFRARE	014486658	74 days	12	11	0	23	4	$113,955	($138,928,792)
24	A	COMPASS,MAGNETIC,UN	011966971	8 months	17,765	5,411	8,809	23,176	22,733	$28,458	($138,900,333)
25	A	MODIFICATION KIT,EL	015536295	16 months	4	4	1	8	3	$8,449,979	($130,450,355)
26	A	NOZZLE SEGMENT,TURB	014186032	11 months	1,067	54	0	1,121	1,238	($27,545,353)	($157,995,708)
27	A	KIT,700 HR PHASE,PH	015463545	12 months	88	16	0	104	148	($12,721,780)	($170,717,488)
28	A	SUPPORT,STRUCTURAL	011531113	21 months	462	46	102	508	1,096	($12,984,810)	($183,702,298)
29	A	MODIFICATION KIT,EL	015536282	15 months	4	3	2	7	9	($2,965,489)	($186,667,787)
30	A	MODIFICATION KIT,EL	015536260	18 months	4	4	1	8	6	$3,379,999	($183,287,788)
31	A	INSTALLATION PKG,EN	015481506	9 months	198	23	0	221	58	$1,204,387	($182,083,401)
32	A	PARTS KIT,TURBINE E	015828014	15 months	330	30	0	360	316	$501,696	($181,581,705)
33	A	ADJUSTOR, TIE DOWN,CA	002121149	6 months	15,229	3,526	7,294	18,755	31,700	($1,046,862)	($182,628,567)
34	A	NOZZLE SEGMENT,TURB	015091990	7.4 months	1,214	346	51	1,560	1,893	($535,797)	($183,164,364)
35	A	BEARING, PLAIN, ROD EN	014170135	16 months	2,032	166	434	2,198	2,436	($614,183)	($183,778,547)
36	A	DAMPER,ROTOR BLADE	012198658	23 months	1,013	142	599	1,155	2,034	($5,015,741)	($188,794,288)
37	A	MODIFICATION KIT,EL	015536279	18 months	2	3	1	5	2	$6,111,268	($182,683,020)
38	A	KIT,STRUCTURAL REPA	013869121	19 months	6	5	0	11	7	$4,044,044	($178,638,976)
39	A	CABLE ASSEMBLY,SPEC	015485758	14 months	266	27	66	293	289	$52,215	($178,586,761)
40	A	NOZZLE SEGMENT,TURB	014948719	11 months	555	155	0	710	938	($863,201)	($179,449,962)
41	A	THERMOCOUPLE,IMMERS	015180319	6 months	1,598	338	292	1,936	2,287	($422,467)	($179,872,429)
42	A	TRANS,RECT ASSEMBLY	014758470	39 months	390	72	3	462	205	$4,881,075	($174,991,354)
43	A	BLADE,TURBINE ROTOR	014520525	4 months	1,344	1,281	1,258	2,625	8,131	($2,443,563)	($177,434,917)
44	A	SPLICE,CONDUCTOR	002717741	2 months	774	291	113,027	1,065	204,013	($10,118,987)	($187,553,904)
45	A	DRIVE ASSEMBLY,INPUT	008364248	18 months	90	77	0	167	31	$2,825,399	($184,728,505)
46	A	BLADE,TURBINE ROTOR	009772120	15 months	630	109	1,592	739	17,415	($114,648,000)	($299,376,505)
47	A	HEAT EXCHANGER,AIR	013417295	13 months	85	17	28	102	129	($582,298)	($299,958,803)
48	A	BLADE,FAN,AIRCRAFT	014725509	7 months	119	208	100	327	250	$484,587	($299,474,216)
49	A	WINDSHIELD PANEL,AI	015655044	16 months	32	10	0	42	71	($1,858,214)	($301,332,430)
50	A	PANEL,STRUCTURAL,AI	012945108	20 months	30	9	0	39	23	$571,863	($300,760,567)

Table 14. Forecast Results versus FY14 DLA Inventory Level

Rank	CLASS	Item Name	NIIN	FY-14 Unit Price	Lead Time (ALT + PLT)	Lead Time Demand Forecast	95% service level forecast = Reorder Point	Actual DLA Reorder Point	Current Holding Cost (18%)	Forecast Holding Cost (18%)	Recommendation Holding Cost (Reduction) or increase	Cumulative Holding Cost (Reduction) or increase
1	A	STABILIZER,VERTICAL	015251263	$782,639	32 months	53	65	168	$19,933,827	$5,423,691	($14,510,135)	($14,510,135)
2	A	BLADE,TURBINE ROTOR	014634340	$4,648	9 months	2,799	3,145	12,414	$9,215,013	$1,460,330	($7,754,683)	($22,264,818)
3	A	THERMOCOUPLE,CONTA(	015075310	$756	12 months	17,086	18,584	22,127	$1,848,511	$1,366,379	($482,131)	($22,746,949)
4	A	FAIRING,AIRCRAFT	011707951	$233	9 months	388	566	963	$32,221	$15,587	($16,634)	($22,763,584)
5	A	PARTS KIT,TURBINE E	015216584	$113,265	12 months	182	192	267	$3,588,232	$2,059,156	($1,529,076)	($24,292,660)
6	A	NOZZLE SEGMENT,TURB	014683897	$2,805	10 months	3,736	4,403	6,438	$2,307,714	$1,280,099	($1,027,614)	($25,320,274)
7	A	MODIFICATION KIT,EL	015536270	$1,230,484	15 months	8	12	13	$1,993,384	$1,771,897	($221,487)	($25,541,762)
8	A	FLAMEHOLDER,AFTERBU	015526939	$42,181	12 months	168	190	243	$1,207,220	$804,813	($402,407)	($25,944,168)
9	A	BLADE,TURBINE ROTOR	015122274	$972	4 months	1,662	3,187	9,304	$1,482,284	$412,163	($1,070,120)	($27,014,288)
10	A	EJECTOR,JET	015404180	$47,384	20 months	286	337	259	$1,449,958	$1,654,658	$204,700	($26,809,588)
11	A	MODIFICATION KIT,EL	015536292	$2,029,435	16 months	3	7	5	$1,278,544	$2,009,140	$730,597	($26,078,992)
12	A	MODIFICATION KIT,EL	015536302	$1,618,119	14 months	7	12	8	$1,310,677	$2,475,723	$1,165,046	($24,913,946)
13	A	PARTS KIT,TURBINE E	016053382	$88,570	13 months	74	100	66	$717,418	$1,004,385	$286,967	($24,626,979)
14	A	MODIFICATION KIT,EL	015536300	$1,617,910	18 months	2	5	2	$291,224	$1,164,895	$873,671	($23,753,308)
15	A	RESCUE UNIT,EMERGEN	014210084	$399	11 months	10,865	14,130	11,020	$401,294	$624,654	$223,360	($23,529,947)
16	A	SEAT,AIRCRAFT	014943019	$38,780	13 months	66	80	97	$446,746	$328,079	($118,667)	($23,648,614)
17	A	BEARING, PLAIN, ROD EN	014170133	$4,235	16 months	1,858	1,928	1,753	$788,218	$761,538	($26,681)	($23,675,295)
18	A	PARTS KIT,GAS TURBI	015522767	$23,049	10 months	55	68	61	$138,985	$168,027	$29,042	($23,646,253)
19	A	BLADE,TURBINE ROTOR	011469445	$1,280	12 months	5,113	6,289	5,451	$666,893	$859,968	$193,075	($23,453,178)
20	A	HEAD,ROTARY RUDDER	015152613	$70,884	25 months	173	195	134	$1,601,270	$1,384,365	($216,905)	($23,670,083)
21	A	BLADE,TURBINE ROTOR	012203928	$169	14 months	29,546	35,402	13,933	$924,342	$627,534	($296,808)	($23,966,891)
22	A	FLAMEHOLDER,AFTERBU	014503755	$490,093	12 months	146	166	210	$12,085,693	$8,204,157	($3,881,537)	($27,848,427)
23	A	ILLUMINATOR,INFRARE	014486658	$5,945	74 days	12	23	4	$14,981	$18,192	$3,210	($27,845,217)
24	A	COMPASS,MAGNETIC,UN	011966971	$64	8 months	17,765	23,176	22,733	$160,156	$165,279	$5,122	($27,840,095)
25	A	MODIFICATION KIT,EL	015536295	$1,689,996	16 months	4	8	3	$912,598	$1,825,195	$912,598	($26,927,497)
26	A	NOZZLE SEGMENT,TURB	014186032	$235,430	11 months	1,067	1,121	1,238	$29,854,925	$24,896,762	($4,958,164)	($31,885,660)
27	A	KIT,700 HR PHASE,PH	015463545	$289,131	12 months	88	104	148	$5,412,539	$3,122,619	($2,289,920)	($34,175,581)
28	A	SUPPORT,STRUCTURAL	011531113	$22,083	21 months	462	508	1,096	$3,438,325	$1,101,059	($2,337,266)	($36,512,847)
29	A	MODIFICATION KIT,EL	015536282	$1,482,745	15 months	4	7	9	$1,868,258	$1,334,470	($533,788)	($37,046,635)
30	A	MODIFICATION KIT,EL	015536260	$1,689,999	18 months	4	8	6	$1,216,800	$1,825,199	$608,400	($36,438,235)
31	A	INSTALLATION PKG,EN	015481506	$7,389	9 months	198	221	58	$317,875	$162,262	($155,612)	($36,593,847)
32	A	PARTS KIT,TURBINE E	015828014	$11,402	15 months	330	360	316	$367,378	$400,217	$32,838	($36,561,009)
33	A	ADJUSTOR, TIE DOWN,CA	002121149	$81	6 months	15,229	18,755	31,700	$350,603	$162,168	($188,435)	($36,749,444)
34	A	NOZZLE SEGMENT,TURB	015091990	$1,609	7.4 months	1,214	1,560	1,893	$372,451	$276,008	($96,443)	($36,845,888)
35	A	BEARING, PLAIN, ROD EN	014170135	$2,581	16 months	2,032	2,198	2,436	$659,704	$549,134	($110,570)	($36,956,458)
36	A	DAMPER,ROTOR BLADE	012198658	$5,706	23 months	1,013	1,155	2,034	$1,568,865	$666,061	($902,803)	($37,859,261)
37	A	MODIFICATION KIT,EL	015536279	$2,037,089	18 months	2	5	2	$366,676	$1,466,704	$1,100,028	($36,759,233)
38	A	KIT,STRUCTURAL REPA	013869121	$1,011,011	19 months	6	11	7	$727,928	$1,455,856	$727,928	($36,031,305)
39	A	CABLE ASSEMBLY,SPEC	015485758	$13,054	14 months	266	293	289	$366,556	$375,955	$9,399	($36,021,906)
40	A	NOZZLE SEGMENT,TURB	014948719	$3,786	11 months	555	710	938	$450,118	$294,740	($155,377)	($36,177,283)
41	A	THERMOCOUPLE,IMMERS	015180319	$1,204	6 months	1,598	1,936	2,287	$322,375	$246,331	($76,044)	($36,253,328)
42	A	TRANS,RECT ASSEMBLY	014758470	$18,993	39 months	390	462	205	$1,299,121	$912,804	($386,318)	($36,639,645)
43	A	BLADE,TURBINE ROTOR	014520525	$444	4 months	1,344	2,625	8,131	$596,123	$156,084	($440,040)	($37,079,685)
44	A	SPLICE,CONDUCTOR	002717741	$50	2 months	774	1,065	204,013	$1,832,634	$6,102	($1,826,532)	($38,906,217)
45	A	DRIVE ASSEMBLY,INPUT	008364248	$20,775	18 months	90	167	31	$388,908	$456,219	$67,311	($38,838,906)
46	A	BLADE,TURBINE ROTOR	009772120	$6,875	15 months	630	739	17,415	$21,161,342	$524,702	($20,636,640)	($59,475,546)
47	A	HEAT EXCHANGER,AIR	013417295	$21,567	13 months	85	102	129	$335,792	$230,978	($104,814)	($59,580,359)
48	A	BLADE,FAN,AIRCRAFT	014725509	$6,293	7 months	119	327	250	$215,787	$303,008	$87,221	($59,493,138)
49	A	WINDSHIELD PANEL,AI	015655044	$64,076	16 months	32	42	71	$634,356	$299,877	($334,478)	($59,827,617)
50	A	PANEL,STRUCTURAL,AI	012945108	$35,741	20 months	30	39	23	$141,536	$154,403	$12,867	($59,814,750)

Table 15. Forecast Results versus FY14 DLA Holding Cost

V. SAFETY STOCK, VARIABILITY, AND LEAD TIME

This chapter discusses safety stock, the impact of variability on inventory level, and how lead time and demand variability combine to determine risk exposure. The chapter ends with a summary.

A. SAFETY STOCK

Safety stock is insurance incorporated into a target service level to guard against the risk of stock-outs due to variable demand during replenishment cycles. Accordingly, "safety stock is a buffer against variability. Except for variability, safety stock would not be needed." Therefore, "safety stock is inventory you do not expect to use, in the sense that on average, you do not use it" (Doerr, 2014).

B. IMPACT OF VARIABILITY ON INVENTORY LEVEL

Calculating protection against demand variability, or the safety-stock quantity, is not an intuitive process. When we discuss demand variability, we are actually referring to the square root of demand variance during the lead time (or, replenishment cycle, which includes admin lead time plus procurement lead time). Because we take the square root of variance, we also take the square root of the lead time to keep the variables (numbers) on the same scale. Figure 41 shows the process of arriving at the safety-stock quantity for the applicable lead time, when lead time is constant and demand is variable (Doerr, 2014)

Variance in demand, with constant lead time

$$\sigma_{\mathrm{d}}^2 = \text{variance in demand per unit time}$$

$$\sigma^2_{\mathrm{ltd,\,constant\_Lead\_time}} = \sigma^2_{\mathrm{d}_1} + \sigma^2_{d_2} + \mathrm{L} + \sigma^2_{d_L} = L\sigma^2_{\mathrm{d}}$$

$$\sigma_{\mathrm{ltd,\,constant\_Lead\_time}} = \sigma_{\mathrm{d}}\sqrt{L}$$

Figure 41. Arriving at Safety Stock Quantity

The formulas above assume product demand follows a normal probability distribution. However, our research introduced complexity into these calculations by employing a range of probability distributions for our forecast model simulations. For example, instead of following a normal distribution, we might hypothesize that demand follows a Poisson distribution in our forecast model. Fortunately, the process of calculating safety stock (SS) under a range of probability distributions is made easy when a Monte Carlo simulation is generated as seen in Figure 42:

SS = target service level (i.e., certainty) less the demand forecast (i.e., mean)

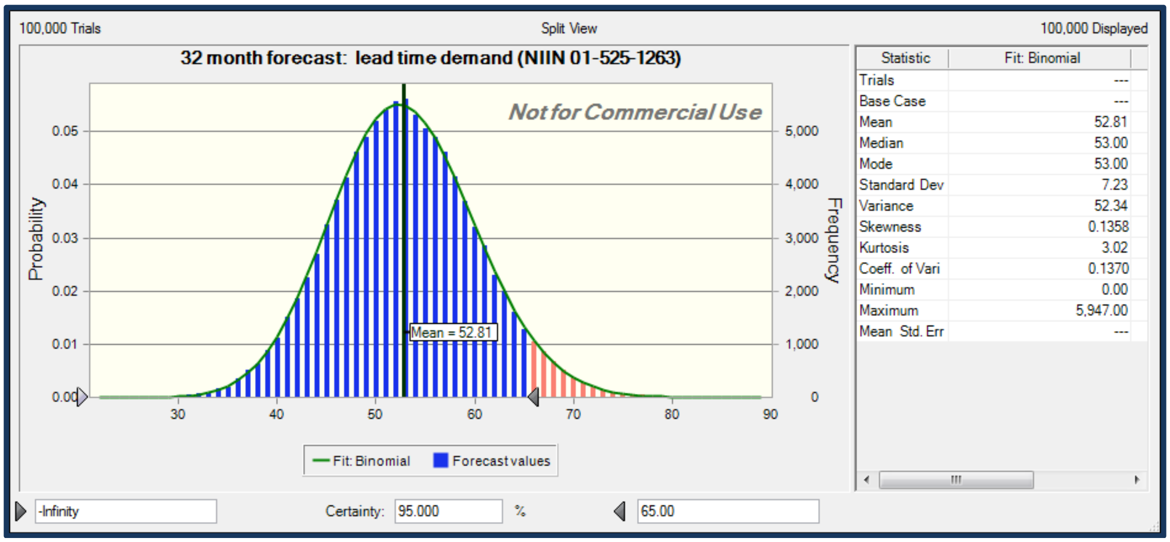


Figure 42. Mean Value of 32 Monte Carlo 32 Month Forecast

An inventory manager must be able to set adequate inventory levels in uncertain market demand. This is established in the form of computing safety stock as follows:

“***A predetermined service level defines safety stock***” (Ferrer, 2014).

	95% service level		65
–	<u>Demand forecast</u>	=	-<u>53</u>
	Safety Stock		12

To clarify, the 95% service level is equal to the reorder point (ROP). Recall from Chapter II that “95% service level” is used interchangeably here for “95% fill rate.” However, these two terms are not normally interchangeable. Ferrer distinguishes service

level as forward looking, “the proportion of ordering cycles without a shortage” and fill rate as backward looking, “the proportion of orders fulfilled from on-hand inventory” (Ferrer, 2014).

Figure 43 helps to visualize the concepts discussed in the previous paragraphs (Doerr, 2014):

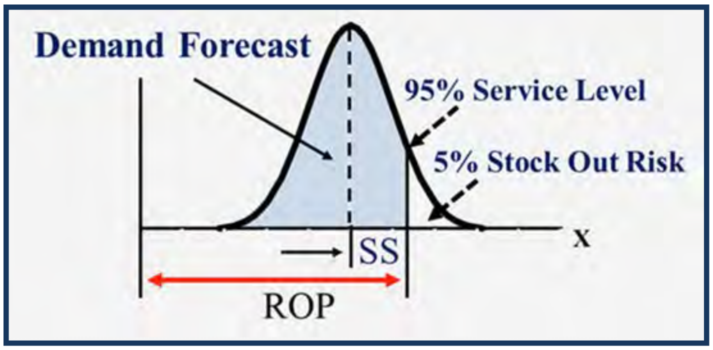


Figure 43. ROP and Safety Stock

The following paragraphs describe two additional important concepts that are not necessarily intuitive, especially because fill rate and service level are used interchangeably in this research.

- **Accurate forecasts** are difficult to achieve due to demand variability. Because service level is a goal (or a predictive value) and fill rates provide a look at the past, “Items with relatively more [demand] variability will have lower [service level]” (Doerr, 2014).

- **Variability** is an inventory cost driver. Items with more demand variability require more safety stock for a target service level.

C. LEAD TIME AND DEMAND VARIABILITY COMBINE TO DETERMINE RISK EXPOSURE

Producing accurate demand forecasts is difficult in the face of variable demand, including forecasts for products with short replenishment lead times. The longer the lead time, the more risk the DLA assumes in meeting customer demand. Therefore, the longer the lead time, the less accurate the forecast model becomes and this knowledge drives the

inventory manager to purchase inventory at very high levels to mitigate risk of stock-outs.

Conversely, negotiating short lead times with suppliers reduces the risk exposure period, and the inventory manager is incentivized to lower inventory levels— resulting in lower material costs.

D. SUMMARY: PUTTING IT ALL TOGETHER

Safety stock is insurance incorporated into a target service level to guard against the risk of stock-outs during replenishment cycles. Higher demand variability results in more required safety stock. Longer lead times compound the need for more safety stock to guard against the risk of stock-outs during the replenishment cycle.

The takeaway is that lead time and demand variability combine in the form of risk exposure. The higher (or longer) the risk exposure, the stronger is the influence on the decision to carry more safety stock. While DLA does not influence demand variability, the organization should use its purchasing power to influence decreased supplier lead times. Additionally, DLA should aggressively seek to decrease internal admin lead time. Decreased lead time lowers risk exposure, and this knowledge should incentivize inventory managers to decrease inventory levels, resulting in decreased material costs.

To reduce inventory costs, the DLA must decrease the lead time (replenishment cycle) and execute accurate forecasts for lead-time demand.

VI. SUMMARY

This chapter summarizes what this research project set out to do, what it actually accomplished, and findings.

A. PROJECT GOALS

We set out to deliver to our project sponsor, DLA, actionable concepts of support for two of its strategic objectives: to right-size operations to peacetime levels and reduce operating costs by $13 billion from 2012–2019. DLA's objectives, simplified for the context of this project, include decreasing material costs and material holding costs, otherwise known as right-sizing inventory.

The actionable concepts of support we set out to deliver include a set of demand forecasting and risk modeling tools and techniques as part of the DLA continuous-planning process to decrease inventory costs in the aviation supply chain—to buy the right stuff in the right quantity at the right time. As demand forecasting alone is an incomplete thought, we also set out to deliver critical inventory policy considerations, including lead-time-demand stock quantity (cycle stock), safety-stock quantity, reorder-point quantity and a risk-modeling technique to achieve two goals: (a) to help meet a target service level and (b) to quantify the risk assumed with the adopted inventory level in the event of stock-outs.

B. PROJECT PERFORMANCE

This project analyzed 4.5 years of sample data from fiscal years 2010–2014, including over 5 million daily materiel requisitions associated with the DLA aviation-supply chain. The tasks performed in this research include:

- Organizing and summarizing historical daily demand data into ABC classification categories, grouping NIINs by highest-to-lowest revenue during FY2013. This data allows the forecaster to focus on the few NIINs that generate the most annual revenue (or, the ones that have the most impact on the budget— see Chapter III).

- Creating visual aids to accelerate understanding of product-demand patterns, in the form of graphs and tables to uncover relationships between raw data elements.
- Performing statistical analysis of demand volumes, variability, lead-time and seasonality.
- Analyzing several time segments for demand probability distribution as a forecasting technique using Monte Carlo simulations.
- Discussing the relationship between inventory levels (cycle stock plus safety stock), lead-time, and variability, and understanding the resulting reorder point to reduce current material costs (or right-sizing current inventory levels).
- Producing Monte Carlo simulations that show demand forecast results, which in turn lead to inputs for replenishment-cycle inventory policy. Such information enables the inventory manager to quantify the risk assumed by the adopted inventory policy, stating upfront the dollar value of the expected stock-out quantity, given a 95% service level policy.

C. FINDINGS

This research produced an abundance of useful lessons for improving the current process for producing demand forecasts, formulating effective inventory policy during replenishment cycles, and understanding (quantifying) stock-out risk:

First, statistical analysis of product demand can yield useful forecast information by fitting demand data into probability distributions. This information, combined with visual representations of summarized demand volume and demand patterns, can be used by the forecaster to easily and quickly organize thoughts into a hypothesis about future demand patterns and probability distribution.

Second, useful forecast models can be produced from analysis of one variable: daily-demand quantity. JMP PRO 10 software easily organized, aggregated, and

generated visual aids for statistical analysis—that is, probability distribution families and associated parameters.

Third, using the probability distributions and associated parameter inputs generated from JMP PRO 10, Crystal Ball software produced user-friendly Monte Carlo simulations that quantified product-demand forecasts, required inventory level with reorder point, and quantified stock-out risk. Thus the process of “dollarizing” both inventory-protection level and stock-out risk became an easy task.

The forecasting theory and process is explained at length in this research. Refer to Chapter II for an explanation of the probability-distribution family. Chapters III and IV and the appendices discuss step-by-step instructions for the forecasting techniques and detailed information on Monte Carlo simulations, inventory-level recommendations, and estimating the dollar value of changes to the status quo. Chapter V summarizes the utility of thinking in terms of replenishment lead time for an inventory policy and explores why that lead time, combined with demand variability, acts as an irresistible influence for higher inventory levels.

In conclusion, because DLA does not influence demand variability, the opportunity to reduce inventory costs resides in its ability to decrease lead time (the replenishment cycle) and its ability to execute accurate forecasts for lead-time demand.

D. CONCLUSION: HOW TO REDUCE INVENTORY COST

To reduce inventory costs, accurate forecasts must be applied to lead-time demand inventory policy (or the inventory level during replenishment cycles). However, automating forecasts is **not** recommended for the few NIINs that have the most impact on annual revenue. Additionally, the DLA must be committed to aggressively reducing lead time for replenishment cycles in order to reduce the exposure period of demand uncertainty. Therefore, the organization must accept responsibility for both nurturing and leaning on a learning curve that narrows the gap between the forecast model and the real world and must continuously improve those internal processes that lead to decreased lead time.

In Chapter II, we stated that the objective for keeping inventory is to meet customer demand at an acceptable service level. A 95% service level is the DLA goal. However, maintaining the right inventory quantity becomes an increasingly complex problem as the supply chain expands the number of unique inventory items—and the DLA aviation supply chain has approximately 55,000 NIINs. Framing the problem as such implies that the labor hours available for managing inventory are a scarce resource. Therefore, an inventory manager should allocate more time to identifying and closely managing those inventory items that have the greatest impact on DLA's cash flows and annual budget. In Chapter III, we described the ABC classification method as a way to separate the few inventory items that have the greatest impact on annual revenue or annual budget. Of course, this method can also be applied to identifying critical spare parts that need to be closely managed (Ferrer, 2014, p. 112).

Though DLA grows richer in automated computing power, the quality of judgment cannot be automated. Thus judgment is both the limiting factor and currently the key factor in maintaining the right quantity of the right stuff. The DLA can leverage expert judgment whenever a forecaster provides the inventory manager with reasonable and useful forecasts based on realistic models. In Chapter IV and the appendices we provide forecasting techniques that enable the production of useful forecast models. While the forecasting process contained therein is not automated, it is nevertheless intuitive and relatively easy to apply using the recommended software. The appendices also present the importance of maintaining a demand tracking signal, which becomes part of the organization's learning curve as it seeks continuously to narrow the gap between the forecast model and real-world product demand.

Accurate forecasts combined with effective inventory policy can help drive down both material cost and holding costs of inventory, despite the existence of variable and intermittent product demand. In Chapter V, we stated that lead time and demand variability combine in the form of risk exposure. Prolonged (higher) risk exposure in the form of longer lead time influences the decision to carry more safety stock. Therefore, while DLA does not influence demand variability, the organization should use its purchasing power to influence decreased supplier lead time. Additionally, DLA should

aggressively seek to decrease admin lead time (internal to the DLA). By so doing, the organization would realize the benefit of less (shorter) risk exposure; and this knowledge should incentivize inventory managers to decrease inventory levels, thus resulting in decreased material costs. In short, Chapter V states that effective inventory management models use accurate demand forecasts for the replenishment lead-time segments as the basis for deciding on the right inventory quantity, as presented in Figure 44:

Inventory Level for a Combined Variable Demand and Constant Lead Time:

Reorder Point = (Lead Time x demand) + Standard Deviation of Demand During Lead Time

Reorder Point = Lead-Time Demand + Safety Stock

Reorder Point = 95% Service Level

Figure 44. Inventory Level Formula

As discussed in Chapter II, an effective inventory-management model minimizes the total cost of providing a target service level. Chapter IV discusses the production of demand forecasts, based on probability distribution of actual demand. Use of the right demand distribution in the forecast model is key to reducing material cost and material holding costs, because the right demand distribution minimizes the perceived required safety stock. First, through statistical analysis, the best-fitting historical demand distribution is used to determine the 95% service level of each NIIN. Second, the 95% service level is different and unique, according to the probability distribution used in the lead-time demand forecast model. Therefore, as described in the appendices, matching the right demand distribution with each NIIN is key to reducing inventory level (cost—with the added benefit of reasonable confidence that the 95% service level will be achieved during the replenishment lead time, or risk-exposure period, as represented in Figure 45.

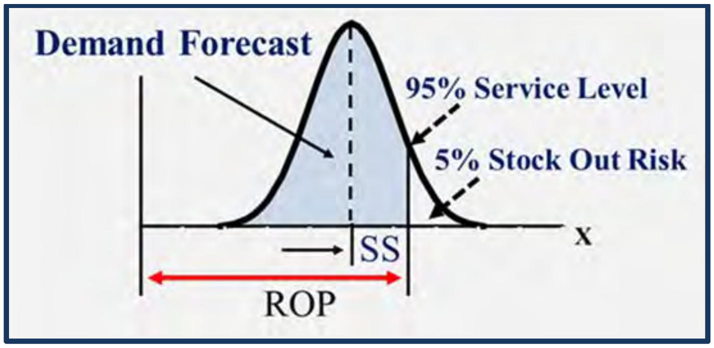


Figure 45. ROP and Safety Stock

In conclusion, because DLA does not influence demand variability, the opportunity to reduce inventory costs resides in its ability to decrease the lead time (replenishment cycle) and execute accurate forecasts for lead-time demand. The next chapter suggests how effective execution of changed inventory policy kindles new recommendations for follow-on research.

VII. RECOMMENDATIONS FOR CONTINUED MBA PROJECT RESEARCH

The intent of the following MBA project research questions is to create value for the customer through improved allocation of DLA’s scarce resources—enabling reduced administrative and supplier lead time—and decreased materiel cost, while improving materiel availability:

A. CLARITY IN DLA PURPOSE AND STRATEGY THROUGH SYSTEMS-DYNAMICS APPROACH

A systems-dynamics approach explains the synthesis of various parts that make up the whole and simulates organizational behavior of a problem (solution) identified within that system. A systems-dynamics approach to this problem should explore the following questions (Abdel-Hamid, 2014, class handout):

1. Where is the leverage?
2. How does change in one variable (feedback loop, stock, flow or delay) affect others?
3. What is the variable’s influence on rest of the system?

B. EMPLOYMENT OF MODELS

Explanations for the above and below research questions should be accompanied by systems-dynamics models that include (1) causal-loop diagrams (2) feedback loops, stock and flow-rate structure, delays, and non-linear relationships, as well as simulations. As of this writing, the Naval Postgraduate School uses Estella software to create systems-dynamics models and simulations.

1. An organization’s purpose statement should be both inspirational and challenging, but most importantly, clear about how it creates value for the customer. How can the DLA purpose statement be transformed to more clearly and effectively inspire and challenge the workforce to work toward a goal that creates customer value?

2. Strategy must clearly identify strategic resources, state how the organization will allocate (leverage) strategic resources, and explain the trade-offs that are implicitly accepted. How can the DLA strategy be improved?

3. Draft and explain a virtuous cycle model, nested under the organization's purpose and strategy.

C. UNDERSTANDING BARRIERS AND INCENTIVIZING THE RIGHT ORGANIZATIONAL BEHAVIOR

The concept for this research is to provide answers that lie in the intersection of several disciplines: supply chain management, operations management, strategic management, organizational behavior and systems dynamics. The following are follow-on research questions to Question 1 above; questions 1 and 2 could be combined into one MBA project or thesis.

1. Explain how the barriers for executing changes in strategy can become opportunities for influencing desired work force behavior. See subparagraph 1.a. and 1.b and use a systems dynamics approach to model the feedback loops stocks, flows, delays and non-linear relationships for this problem.

2. Explain and simulate the behavior of these barriers for executing policy change and explain (simulate) proposed intervention (workforce incentives) to counteract or self-correct barriers.

D. MODELING AND SIMULATION OF A WORLD-CLASS SUPPLY CHAIN THAT MINIMIZES LEAD TIME AND THE BULLWHIP EFFECT.

According to Doerr, "If demand variability is not absorbed in safety stock or the supplier's safety capacity, then demand variability will be absorbed in lead time" at the expense of both the customer and DLA (Doerr, 2014, class handout).

See subparagraphs 1.a and 1.b for background of systems dynamics. The concept for this research is to provide answers that lie in the intersection of several disciplines:

operations management, supply chain management, logistics engineering, logistics risk management and systems dynamics:

1. Build a supply chain model with self-corrective feedback loops for minimizing effects of the bullwhip effect (variable demand and or lead time).

2. Build a warehousing and distribution network model that is inspired by an actual, world-class supply chain that minimizes delivery lead time, pools inventory risk and leverages technology to minimize delivery lead time.

3. Pinpoint the variables that contribute to long lead time which accompany increased demand uncertainty / risk of stocking out. Where is the leverage?

    - Incentivize the vendor(s) to decrease the production (procurement) lead time.
    - Incentivize DLA employees to decrease the admin lead time.
    - Incentivize feedback loops from DLA planners to forecasters to contracting officers.

E. QUALITATIVE APPROACH FOR IMPROVING DEMAND FORECASTING BASED ON STATISTICAL ANALYSIS

The research should investigate, from a macroeconomics point of view, the leading indicators for a shift in demand before it happens.

1. How can DLA leverage the knowledge of an incoming fiscal year’s national defense budget to produce more accurate forecasts that are based on statistical analysis?

2. From a historical perspective, model and simulate the behavior of demand after the declaration of war- during the execution phase for DLA supply chains.

3. Model and simulate the behavior of demand for DLA supply chains during and after the redeployment phase of war.

4. Model and simulate demand for spare parts when forces are maneuvered for extended operations in a different climate and elevation.

APPENDIX A. LEAD-TIME DEMAND FORECAST FOR NIIN 011707951 VERTICAL STABILIZER

Information found in this appendix regarding product demand forecast for the vertical stabilizer includes:

A. Statistical analysis of product demand

B. Observations from the statistical analysis

C. Lead-time-demand forecast: an input for inventory policy

D. Inventory Policy Formulation

E. Conditional value at risk analysis

A. STATISTICAL ANALYSIS OF PRODUCT DEMAND

Demand for this product was sporadic during FY10 to FY11 and highly variable during FY12 and FY13.

- Figure 46 indicates an outlier value in September 2013 (month: 2013–2012).
- Figure 47 shows a decrease in demand during the period Fiscal Year 2012 to Fiscal Year 2013.
- Figure 48 shows the effect of demand when the outlier values have been removed: the overall monthly mean demand has decreased by one unit in Fiscal Year 2013. When demand is low, this small difference in mean monthly demand is a driver for an accurate forecast.

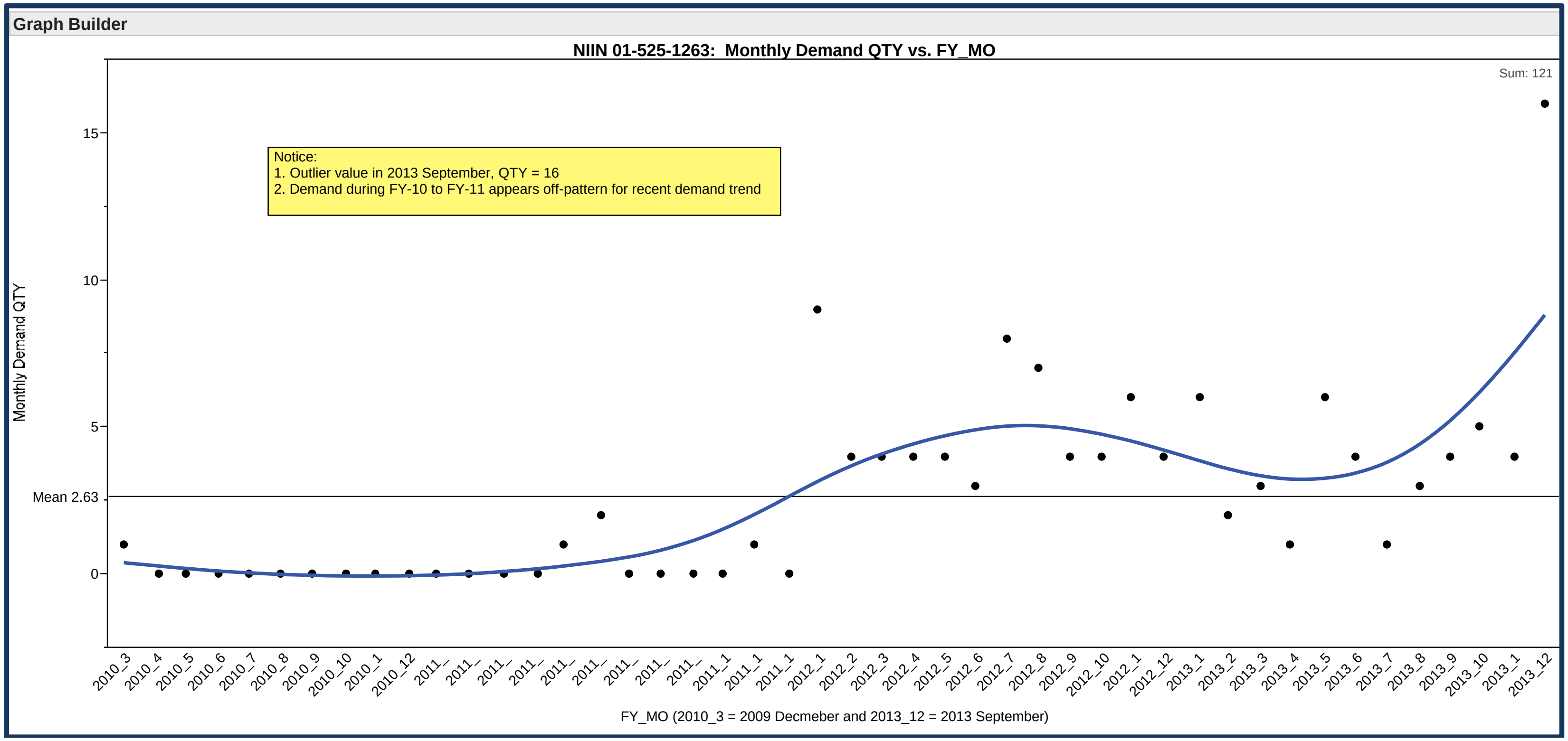


Figure 46. NIIN 01-525-1263 Monthly Demand FY 10 – FY 13

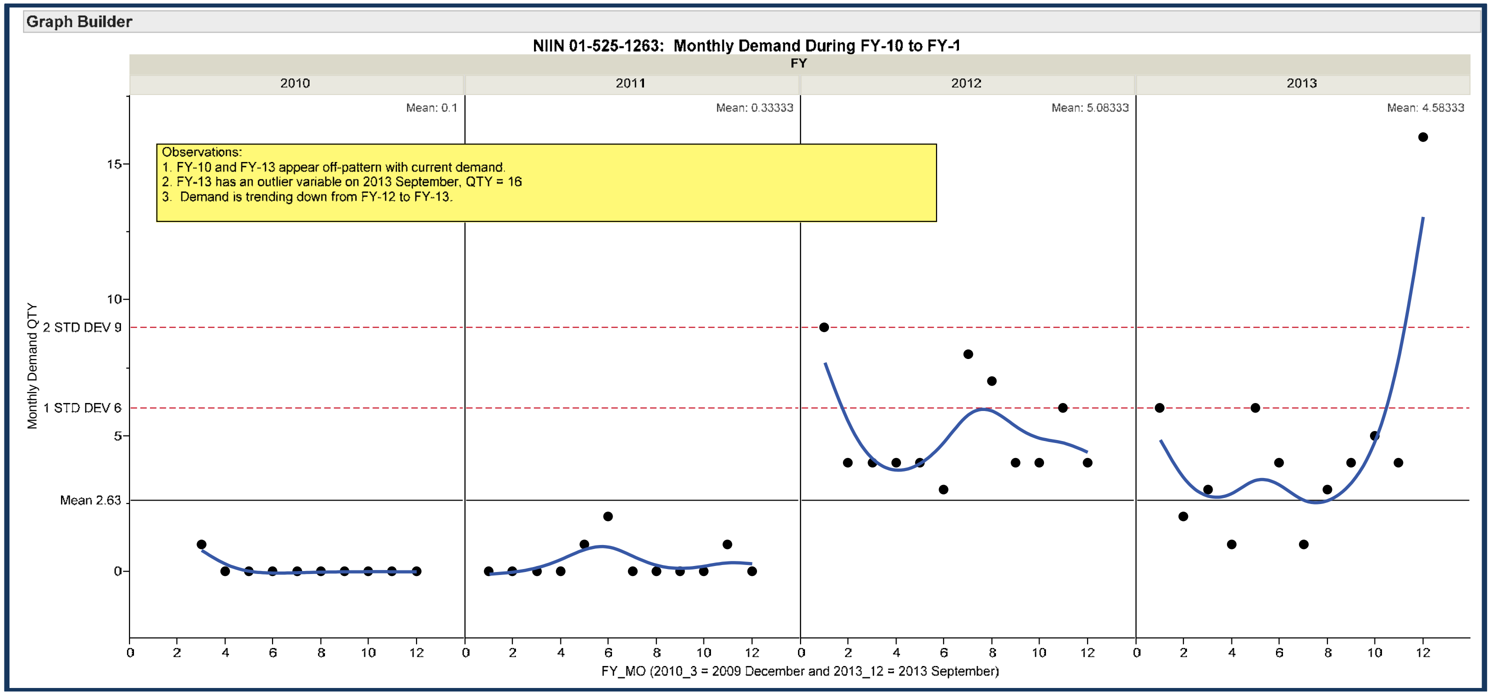


Figure 47. NIIN 01-525-1263 Monthly Demand FY10 – FY13

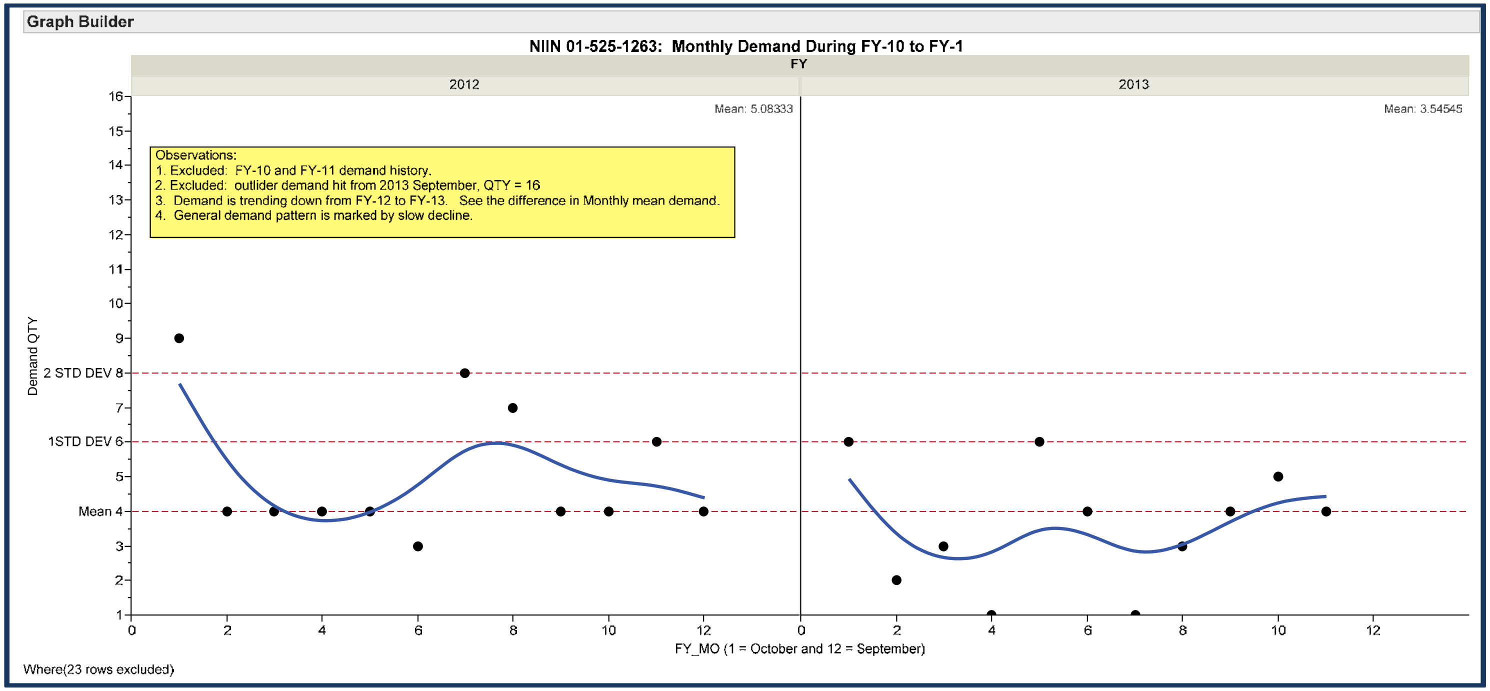
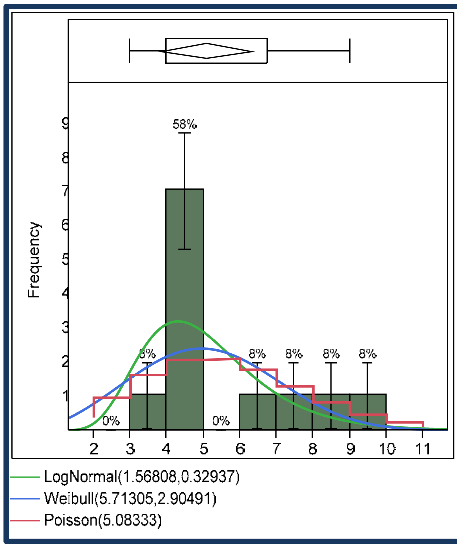


Figure 48. NIIN 01-525-1263 Monthly Demand After Outlier Exclusion FY12 to FY13

- **Probability Distribution Analysis**

Among the highlights in the distribution analysis, note that various probability distributions have been fit to the demand data by fiscal year.

As shown in figures 49 – 50, Poisson distribution has the best goodness-of-fit score for demand data from both FY12 and FY13 (see the data in the red caption boxes).



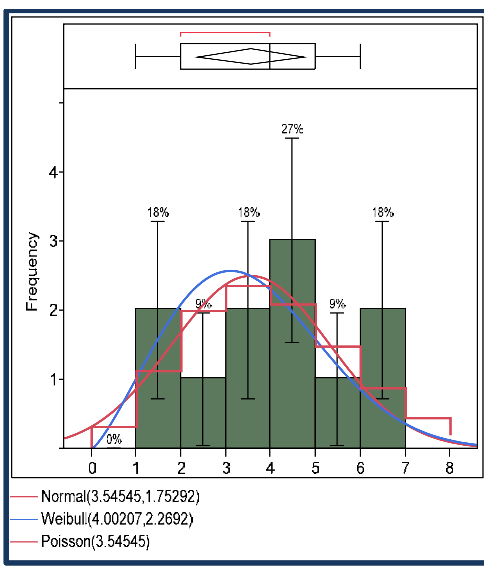
Quantiles: FY-12 Monthly Demand, NIIN 01-525-1263

100.0%	maximum	9
99.5%		9
97.5%		9
90.0%		8.7
75.0%	quartile	6.75
50.0%	median	4
25.0%	quartile	4
10.0%		3.3
2.5%		3
0.5%		3
0.0%	minimum	3

Summary Statistics

Mean	5.0833333
Std Dev	1.9286516
Std Err Mean	0.5567538
Upper 95% Mean	6.3087401
Lower 95% Mean	3.8579266
N	12
Variance	3.719697
Skewness	1.1368917
Kurtosis	-0.043036
Median	4
Mode	4
Range	6
Interquartile Range	2.75

Figure 49. NIIN 01-525-1263 FY 12 Demand Data Histogram



Quantiles: FY-13 Monthly Demand, NIIN 01-525-1263

100.0%	maximum	6
99.5%		6
97.5%		6
90.0%		6
75.0%	quartile	5
50.0%	median	4
25.0%	quartile	2
10.0%		1
2.5%		1
0.5%		1
0.0%	minimum	1

Summary Statistics

Mean	3.5454545
Std Dev	1.7529196
Std Err Mean	0.5285252
Upper 95% Mean	4.723082
Lower 95% Mean	2.3678271
N	11
Variance	3.0727273
Skewness	-0.092266
Kurtosis	-0.923054
Median	4
Mode	4
Range	5
Interquartile Range	3

Figure 50. NIIN 01-525-1263 FY 13 Demand Fit Histogram

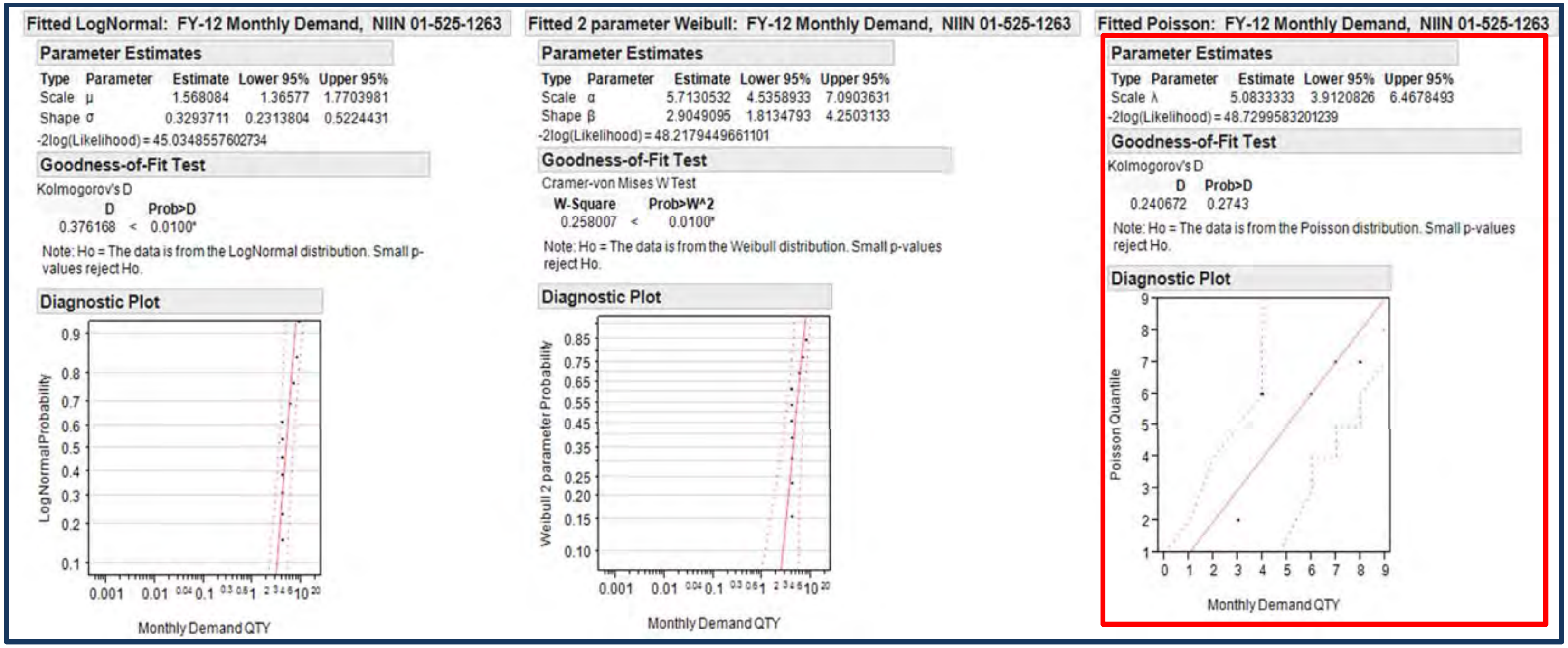


Figure 51. NIIN 01-525-1263 FY 12 Goodness-Of-Fit Tests

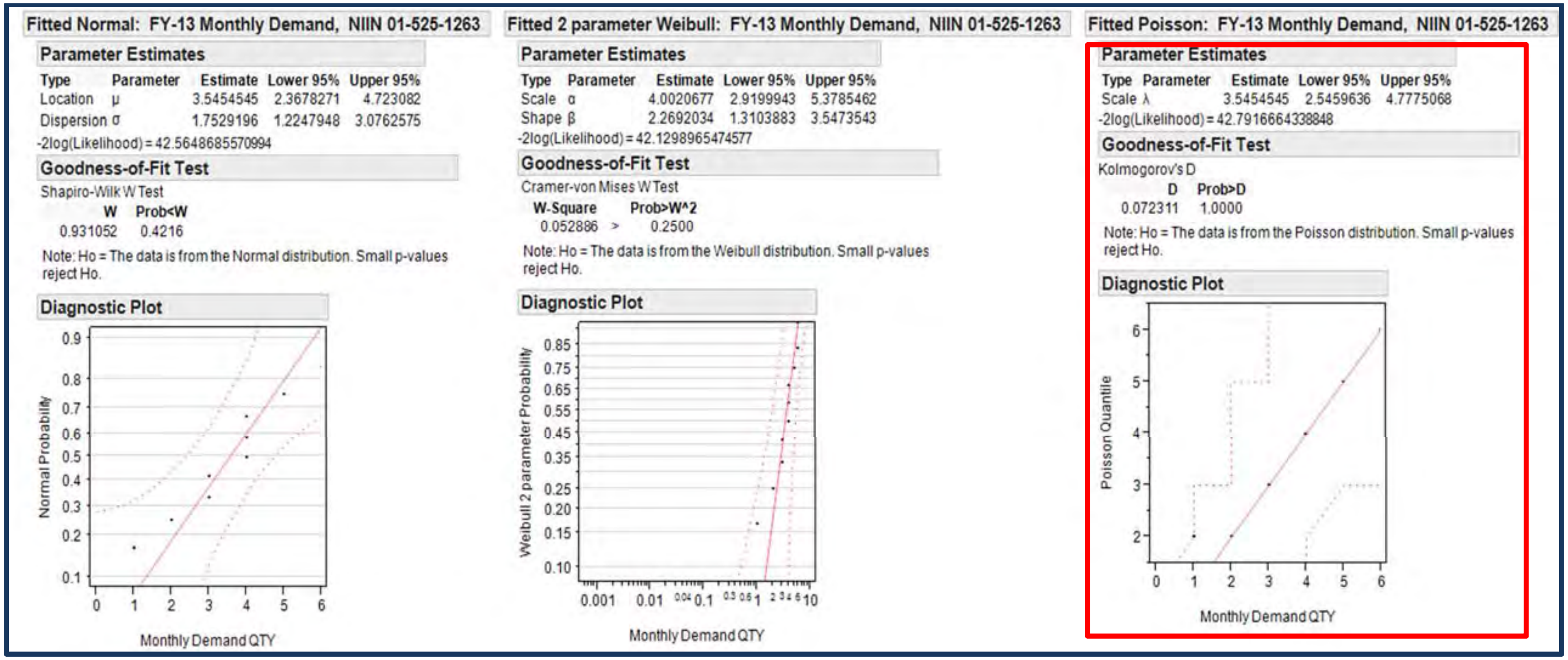


Figure 52. NIIN 01-525-1263 FY 13 Goodness-Of-Fit Tests

In the Prediction Interval section in Figure 53, the lower-to-upper range in both the mean (μ) value and standard deviation is relatively large. Since a downtrend seems to dominate the pattern of product demand from FY12 to FY13, the lower confidence level could be the more valid predictor value.

Prediction Interval: FY-12
Monthly Demand, NIIN 01-525-1263

Parameter	Future N	Lower PI	Upper PI	1-Alpha
Individual	6	-1.35666	11.52333	0.950
Mean	6	2.960867	7.2058	0.950
Std Dev	6	0.752564	3.878459	0.950

Prediction Interval: FY-13
Monthly Demand, NIIN 01-525-1263

Parameter	Future N	Lower PI	Upper PI	1-Alpha
Individual	6	-2.454	9.544908	0.950
Mean	6	1.563212	5.527697	0.950
Std Dev	6	0.681335	3.607816	0.950

Figure 53. NIIN 01-525-1263 Prediction Intervals FY 12 and FY13

- **Gaussian and Time-series sensitivity analysis for demand during FY12 and FY13**

Demand during each fiscal year is highly variable (see the standard deviation value). However, the mean value and standard deviation are the strongest indicators of what demand quantity could be during lead-time demand (demand between replenishment cycles).

Several analytical highlights are shown in Figure 54. The Gaussian model was run using the Poisson parameter (scale = 3.55) and the result was a six-month forecast of 21 units of demand. Second, two of the time-series models yielded six-month forecasts equal to the Gaussian model (8,196 units). Two time-series models yielded six-month forecasts of 21 units. Third, the 95% service level quantity of a Poisson distribution forecast would be significantly higher than the mean value of the Gaussian forecast (21 units). That would require maintaining a high inventory for safety stock (95% service level minus mean value of forecast = safety stock). Due to this third point, and because the trend is slowing demand across fiscal years, we favor using the Lower 95% Parameter Estimate in our Crystal Ball (normal distribution) forecast simulation: scale = 2.55 (see Figure 54, "Fitted Poisson for FY13 Monthly Demand."

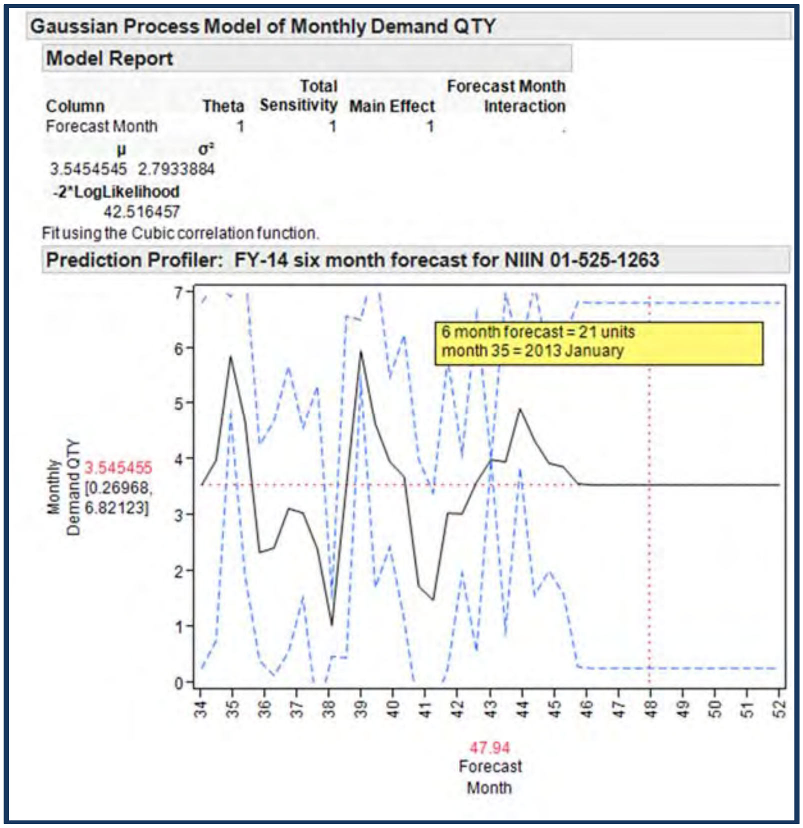


Figure 54. NIIN 01-525-1263 Gaussian Forecast Model

The effects of exponential smoothing are presented in Figures 55 – 58.

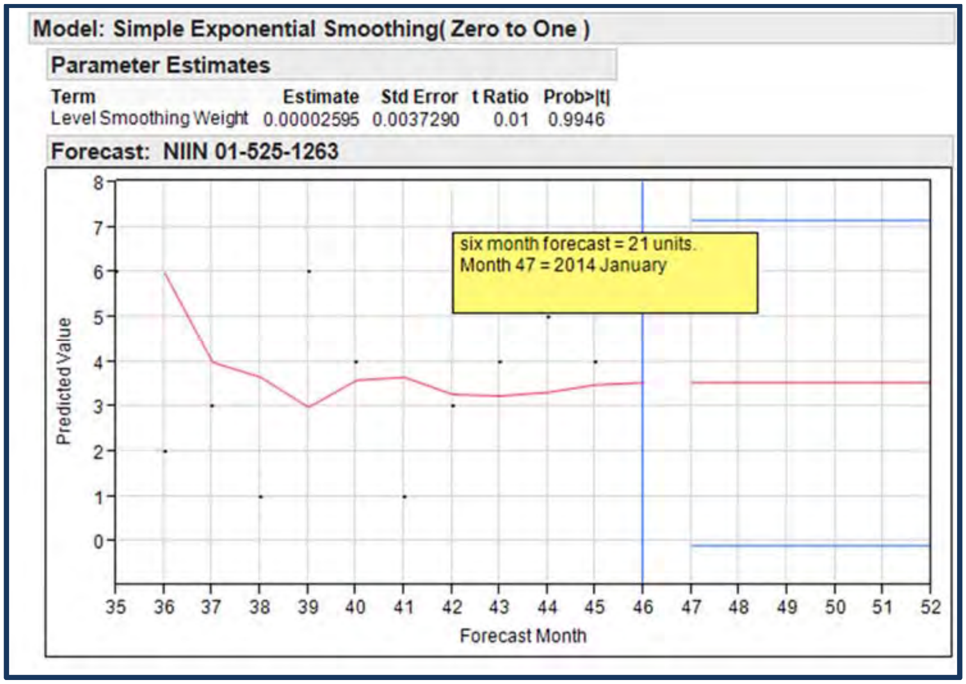


Figure 55. NIIN 01-525-1263 Simple Exponential Smoothing

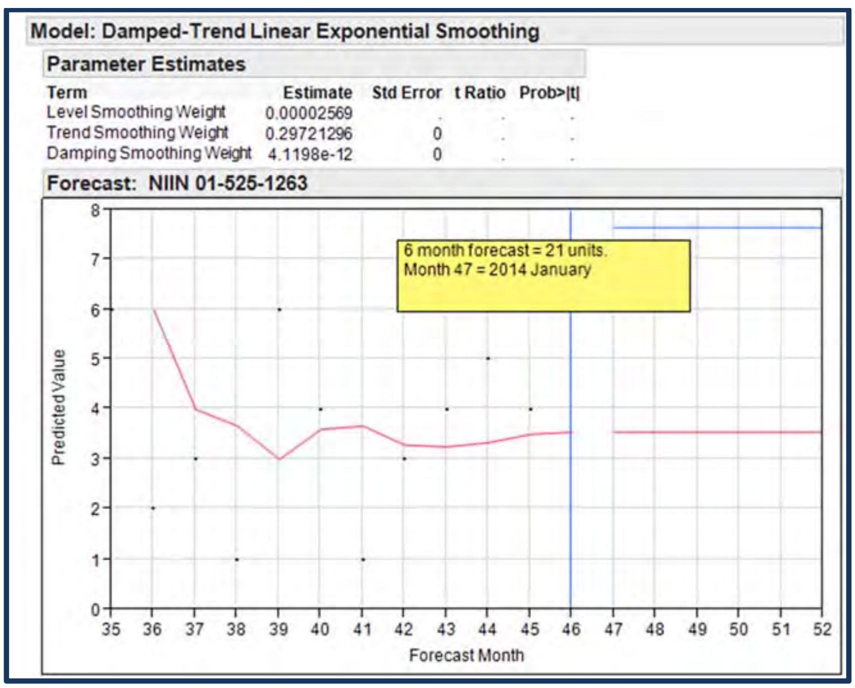


Figure 56. NIIN 01-525-1263 Damped Trend Linear Exponential Smoothing

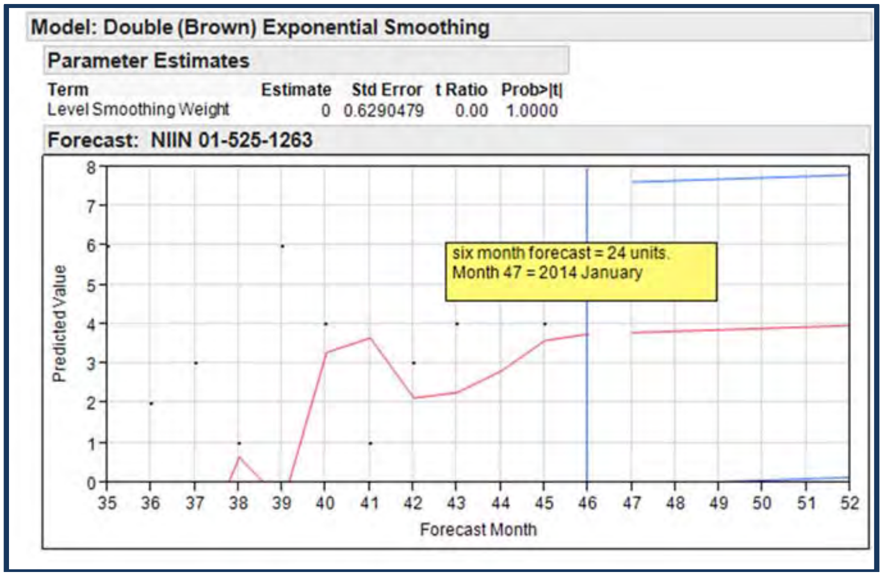


Figure 57. NIIN 01-525-1263 Double (Brown) Exponential Smoothing

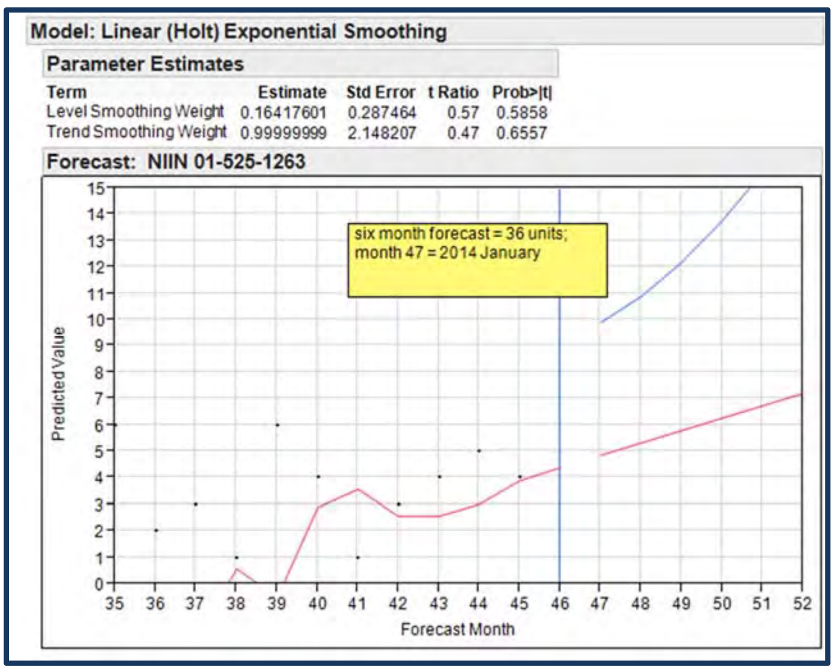


Figure 58. NIIN 01-525-1263 Linear (Holt) Exponential Smoothing

B. OBSERVATIONS FROM STATISTICAL ANALYSIS

According to JMP statistical analysis, the demand for this NIIN appeared non-static and highly variable. An adequate probability distribution fit was found—the Poisson distribution had the best goodness of fit (highest p-value for a distribution fit).

C. LEAD-TIME DEMAND FORECAST (32 MONTHS) USING THE MONTE CARLO SIMULATION

- **First Forecast**

We assume that this forecast was conducted at the end of FY13.

- We used an eleven-month window from FY13 and excluded one outlier value in September 2013.
- The Poisson distribution parameter rate = 2.55 (see prediction interval-section of the univariate analysis).
- Lead-time demand during 32 months = 82 units.
- 95% service level = lead-time demand + safety stock = 97 units

The Monte Carlo simulations in Figures 59, 60, and 61 show various forecasts from 32 months (lead time), 12 months (FY14) and 6 months (to gauge forecast model performance against the actual FY14 demand). Actual demand data for October 2013 to March 2014 was known. Therefore, we used the six-month forecast to gauge performance (forecast error between the model and the real world).

- **Observations from the First Forecast**

It is assumed the observations from the first forecast were compiled after a 6 month lapse, at the end of March 2014. The graph below shows a forecast error of 50%; yet if the product-demand forecast above was used to formulate inventory policy, DLA would still realize significant inventory cost reductions, because the actual inventory is high, as shown in Figure 61 (see inventory-policy section below).

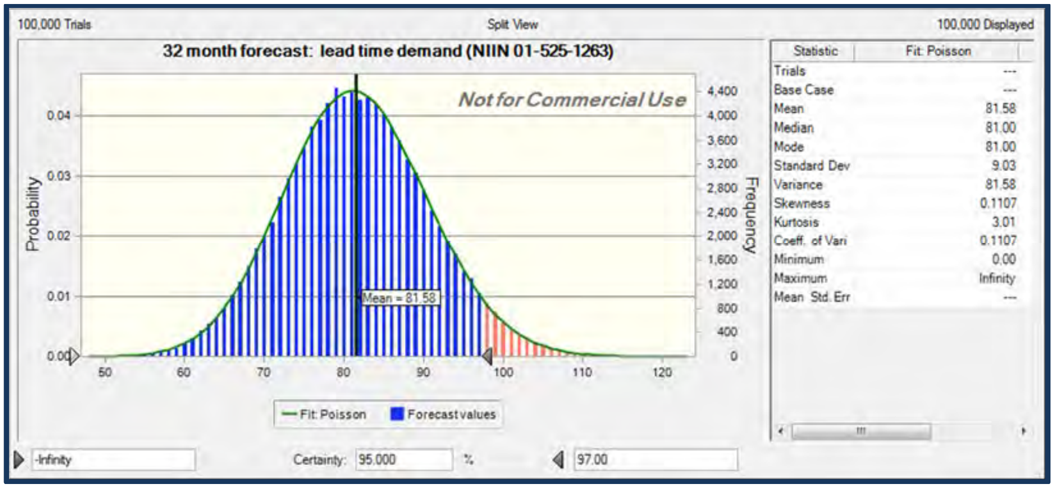


Figure 59. NIIN 01-525-1263 32-Month Forecast Simulation

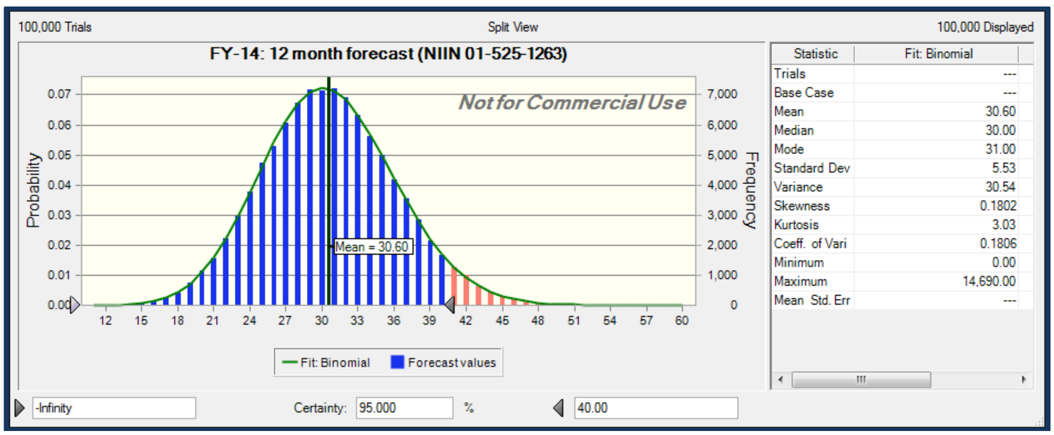


Figure 60. NIIN 01-525-1263 12-Month Forecast Simulation

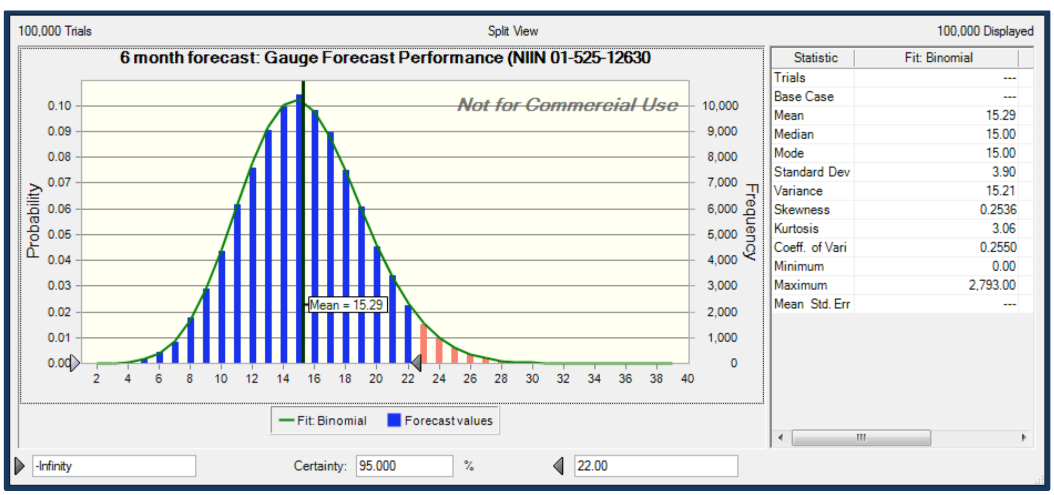


Figure 61. NIIN 01-525-1263 6 Month Forecast Simulation

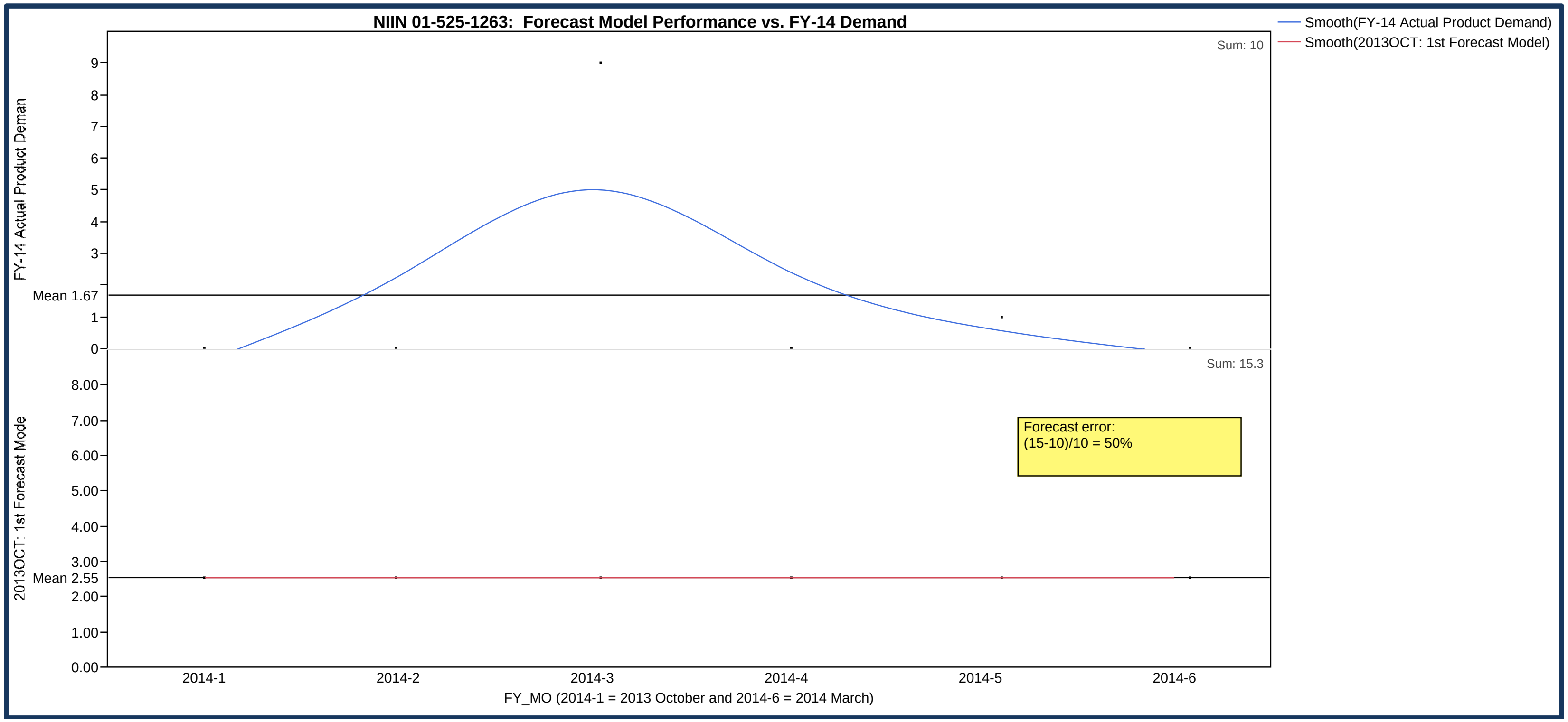


Figure 62. NIIN 01-525-1263 Monte Carlo Forecast Model versus Actual FY 14 Demand (50% error)

Table 16 compares the results of the first forecast with actual product demand during the first six months of FY14. The lead-time demand forecast is also provided (shaded gray). Notice the forecast reorder point is 97 units.

Six Month Forecast: Comparison of the forecast model vs. actual demand			
		Average	Average
FY_MO	FY-14 Actual Product Demand	2013OCT: 1st Forecast Model	2014APR: 2nd Forecast Model
2014-1	0	2.55	
2014-2	0	2.55	
2014-3	9	2.55	
2014-4	0	2.55	
2014-5	1	2.55	
2014-6	0	2.55	
Total	10	15.29	0
		Oct. 2013 six month forecast error:	
Delta forecast #1	5.29	ABS(15-10)/10 = 50%	Apr. 2014 six month forecast error:

All forecasts:		
FY 2014, six months:	15	
FY 2014, twelve months:	31	
Lead Time demand, 31 months:	82	
Reorder Point:	97	

The market for this product is non-static, characterized by shifting conditions.

Table 16. NIIN 01-252-1263 Comparison First Forecast versus Actual Demand

- **Second Forecast**

It is assumed this forecast was conducted on the first week of April 2014 (mid-year forecast update).

We continued to use the Poisson distribution, but changed the parameter: scale = 1.65 (because the mean demand during the first six months of FY14 was 1.67 units / month). Again, we used FY14 QTR 1 and QTR 2 demand data to gauge forecast model performance.

The forecasts simulations are shown in Figures 63 – 65.

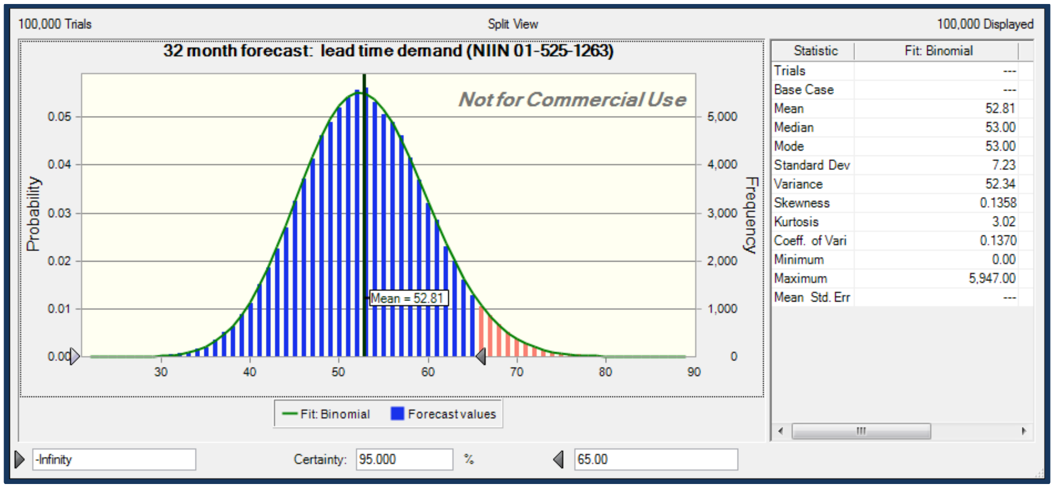


Figure 63. NIIN 01-525-1263 32-Month Forecast Simulation (2nd)

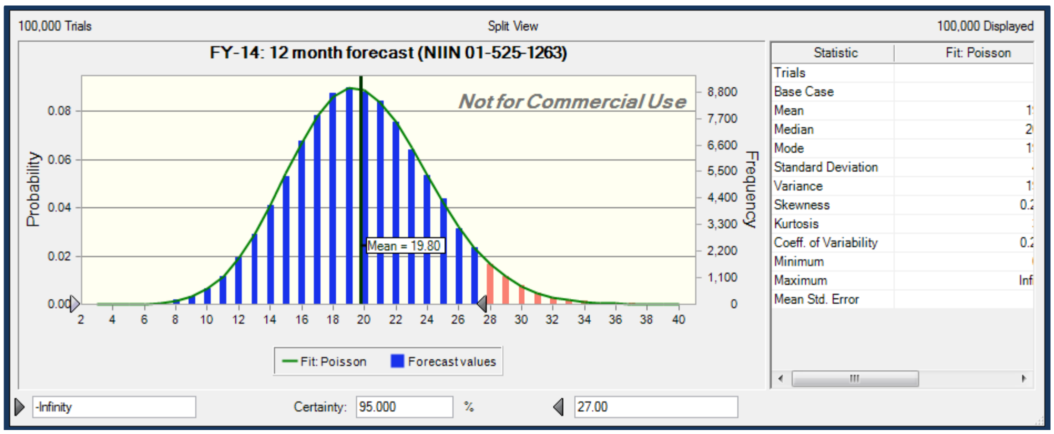


Figure 64. NIIN 01-525-1263 12-Month Forecast Simulation (2nd)

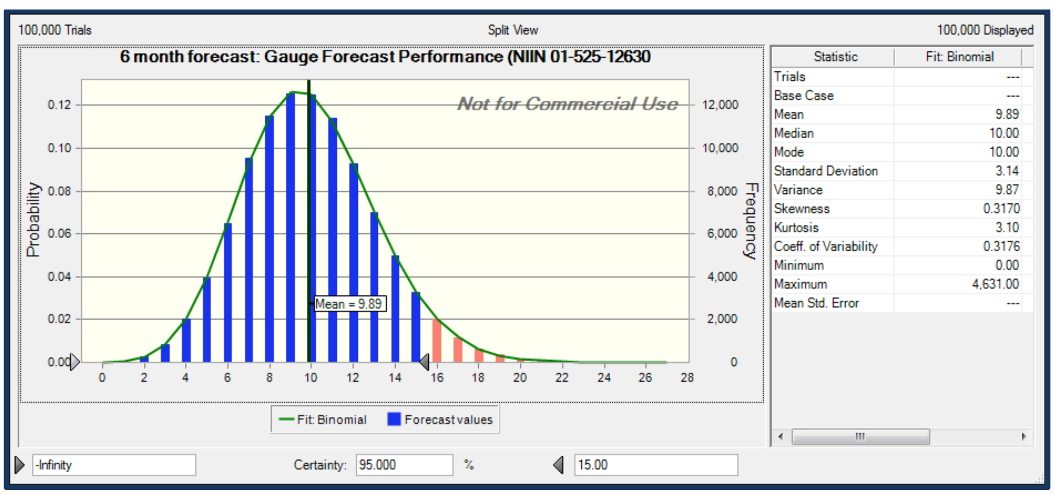


Figure 65. NIIN 01-525-1263 6-Month Forecast Simulation (2nd)

- **Observations from the Second Forecast**

The graph in Figure 66 shows a forecast error = 0%, and if the forecast in Figure 63 was used to formulate inventory policy, DLA would realize significant inventory cost reductions, because the actual inventory is high (see inventory-policy section below).

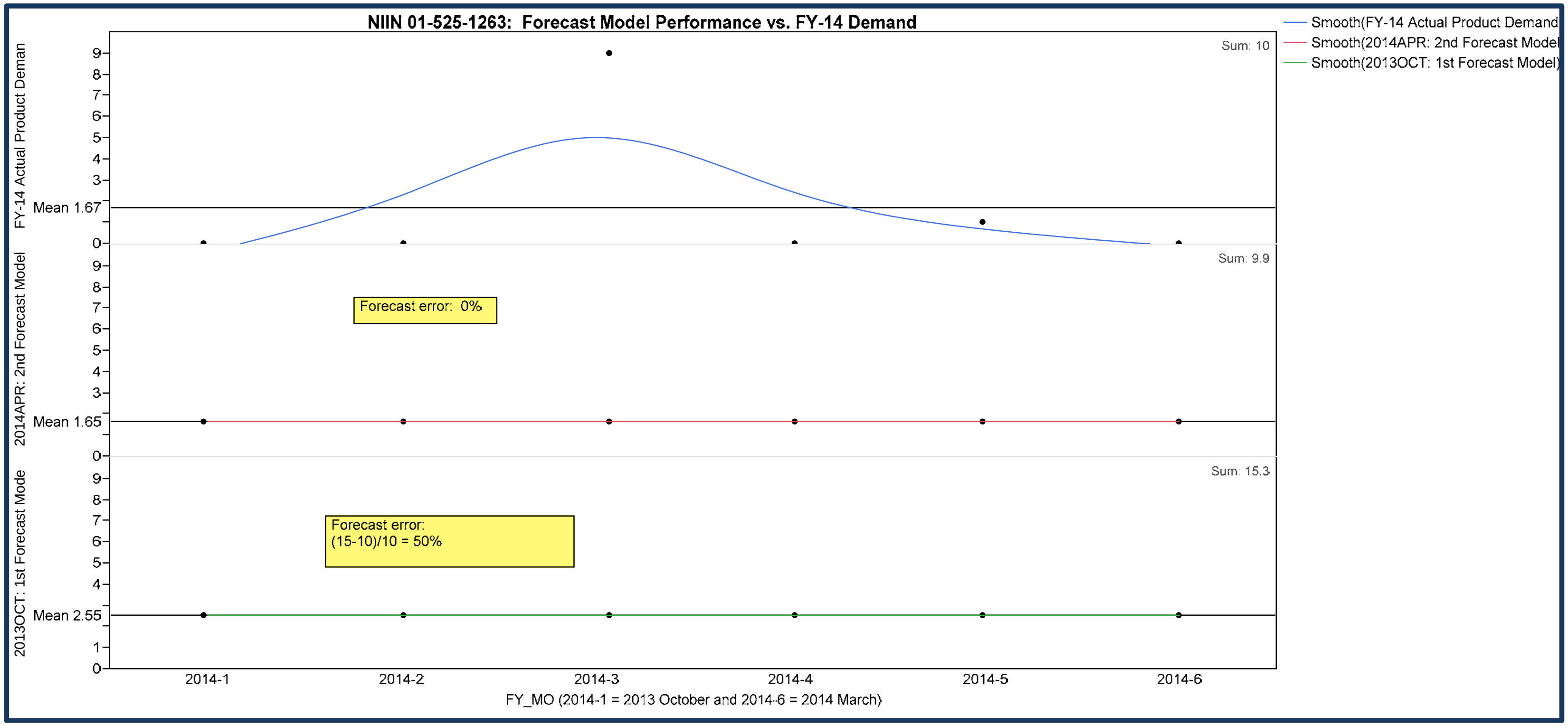


Figure 66. NIIN 01-525-1263 Monte Carlo Forecast Model versus Actual FY 14 Demand (0 % error)

Table 17 shows the improved forecast accuracy from 50% (October 2013 model) to 0% (April 2014 model). The reorder point is 65 units.

Six Month Forecast: Comparison of the forecast model vs. actual demand			
		Average	Average
FY_MO	**FY-14 Actual Product Demand**	**2013OCT: 1st Forecast Model**	**2014APR: 2nd Forecast Model**
2014-1	0	2.55	1.65
2014-2	0	2.55	1.65
2014-3	9	2.55	1.65
2014-4	0	2.55	1.65
2014-5	1	2.55	1.65
2014-6	0	2.55	1.65
Total	**10**	**15.29**	**9.91**
		Oct. 2013 six month forecast error:	
Delta forecast #1	5.29	ABS(15-10)/10 = ***50%***	Apr. 2014 six month forecast error:
Delta forecast #2	0.09		error: ABS(10-10)/10= ***0%***
	All forecasts:		
	FY 2014, six months:	15	10
	FY 2014, twelve months:	31	20
	Lead Time demand, 32 months	***82***	***53***
	Reorder Point:	97	65

The market for this product is non-static, characterized by shifting conditions.

The Apr-14 forecast used months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.

Table 17. NIIN 01-252-1263 Comparison Second Forecast versus Actual Demand

D. INVENTORY-POLICY FORMULATION: AS CONDITIONS CHANGE, SO MUST INVENTORY POLICY

The results of the Monte Carlo simulations provide guidance for inventory-policy change. First, whereas DLA inventory policy for FY14 calls for a reorder point of 168 units, the October 2013 forecast called for a reorder point of 97 units. That is a difference of 71. At a FY14 price of about $780 thousand per unit, the inventory cost reduction would be $19 million (with selling price used in the absence of cost price).

Second, the April 2014 forecast calls for further reducing the reorder point from 168 units to 65 units, a difference of 103. The inventory cost reduction would be $80 million (selling price used in lieu of cost), as shown in Table 18.

Evolving Inventory Policy: Narrowing the gap beween the model and the real world			
	Actual DLA QTY	1st forecast	2nd forecast
Effective date:	FY 14	Oct-13	Apr-14
Forecast		82	53
Safety Stock:	32	15	12
Reorder Point:	168	97	65
The market for this product is non-static, characterized by shifting conditions and uncertainty.			
The Apr-14 forecast used 6 months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.			
FY-14 unit price	Delta	cost savings	cost increase
$782,639	103	$80,611,862	

Table 18. NIIN 01-525-1263 Forecast Model versus Real World Demand

- **Inventory-Management Assumption**

Since this NIIN is a class-A item, it should be managed with a continuous inventory policy, due to this product's impact on (potential) overall annual revenue.

JMP online software training provides the insight, "All [forecast] models are wrong, but some are useful. Figure 67 states that the organization's performance is a function of their learning curve." See how this statement applies to inventory policy formulation in the next section as it discusses the cost reduction benefit of reducing lead time.

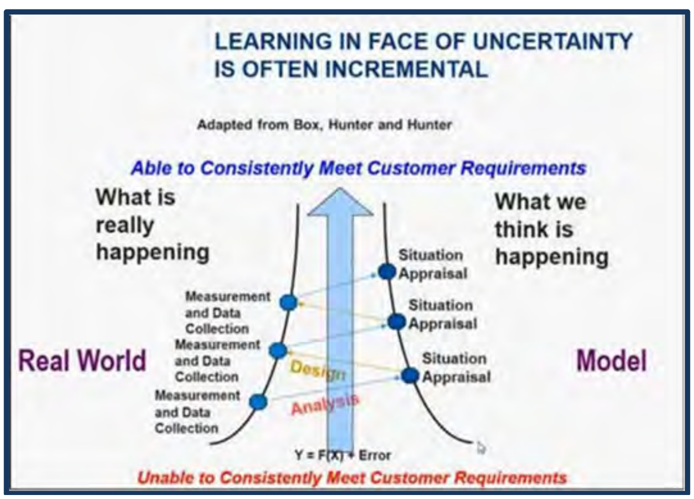


Figure 67. Learning curve, adopted from Exploring Best Practices in Design of Experiments SAS Institute (Webinar 2014)

E. CONDITIONAL-VALUE-AT-RISK ANALYSIS

Figures 68 and 69 shows the lead-time demand forecast. The 95% service level is shaded blue, and the value of this area under the demand curve is 65 units. The remaining 5% is the conditional value at risk (right tail of the distribution curve). The second graph represents the range of values of the conditional value at risk (if stock runs out, what is the expected amount?).

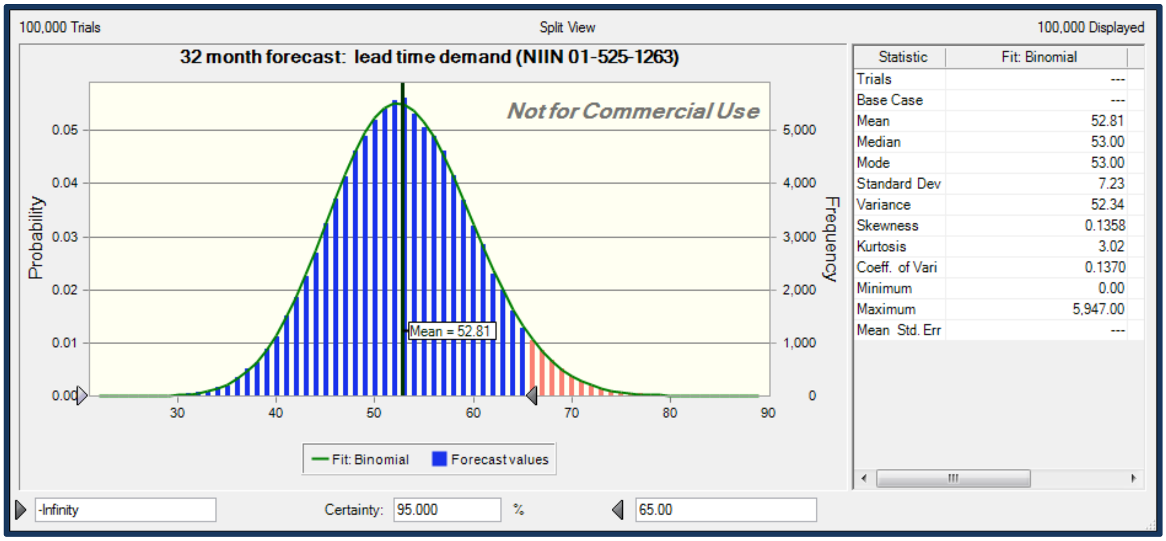


Figure 68. NIIN 01-525-1263 32-Month Lead Time Demand Forecast

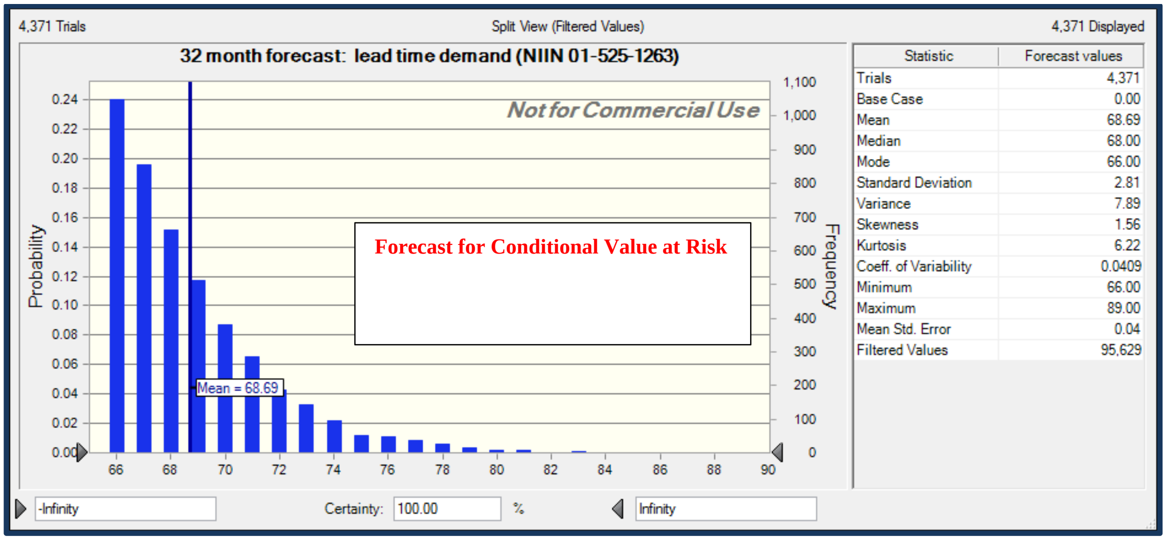


Figure 69. NIIN 01-525-1263 Conditional Value at Risk

The conclusions from the Monte Carlo simulation are summarized in Table 19.

The average lead-time demand forecast (50% probability	**53 units** (lead time = 32 months)
A 95% fill rate quantity equals	**65 units** of inventory
Conditional risk: If demand exceeds stock on hand during the replenishment cycle, the expected shortage is	**4 units** (see forecast right tail distribution: 69 - 65 = 4)
How bad can things get if there is a stock out? The maximum shortage forecasted is	**24 units** (89– 65 = 24)

Table 19. NIIN 01-525-1263 Lead Time Demand Forecast and Stock out Risk Analysis Summary Table

a. Improving the Organization's Learning Curve

The organizations should produce demand forecasts and risk analysis for this NIIN on a quarterly basis at least and adjust the inventory policy (reorder point and safety stock levels) as required. This implies integrated planning with the contracting officer and item manager for negotiating the right procurement contract with the supplier(s).

b. Learning-Curve Potential

Table 20 and Figure 70 illustrate that lead time for this NIIN shifts annually, but not in a decreasing trend. Reducing the replenishment lead time (admin + procurement) would reduce the exposure period of demand uncertainty and would likely lead to lower safety stock and reorder points, and thus, lower inventory costs.

Lead Time (FY-14)	NIIN 01-525-1263
procurement lead time days:	840
admin lead time days:	120
total days:	960
months	**32**

Table 20. NIIN 01-525-1263 Admin and Procurement Lead Time

Tabulate: NIIN 01-525-1263

								qty_req	Revenue	alt				plt		
FY	Quarter	FY_MO	FY_MO Series	Calendar Month	niin	itm_name	std_u_price	Sum	Sum	30	84	90	120	540	840	999
2010	1	2010_3	3	12	015251263	STABILIZER,VERTICAL	$644,655.54	1	$644,655.54	0	0	1	0	0	0	1
2011	2	2011_5	5	2	015251263	STABILIZER,VERTICAL	$833,496.88	1	$833,496.88	1	0	0	0	1	0	0
		2011_6	6	3	015251263	STABILIZER,VERTICAL	$833,496.88	2	$1,666,993.76	2	0	0	0	2	0	0
	4	2011_11	11	8	015251263	STABILIZER,VERTICAL	$814,849.15	1	$814,849.15	1	0	0	0	0	1	0
2012	1	2012_1	1	10	015251263	STABILIZER,VERTICAL	$814,849.15	9	$7,333,642.35	5	0	0	0	0	5	0
		2012_2	2	11	015251263	STABILIZER,VERTICAL	$814,849.15	4	$3,259,396.60	2	0	0	0	0	2	0
		2012_3	3	12	015251263	STABILIZER,VERTICAL	$814,849.15	4	$3,259,396.60	3	0	0	0	0	3	0
	2	2012_4	4	1	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	1	0	0	0	0	1	0
		2012_5	5	2	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	2	0	0	0	0	2	0
		2012_6	6	3	015251263	STABILIZER,VERTICAL	$786,329.43	3	$2,358,988.29	2	0	0	0	0	2	0
	3	2012_7	7	4	015251263	STABILIZER,VERTICAL	$786,329.43	8	$6,290,635.44	5	0	0	0	0	5	0
		2012_8	8	5	015251263	STABILIZER,VERTICAL	$786,329.43	7	$5,504,306.01	3	0	0	0	0	3	0
		2012_9	9	6	015251263	STABILIZER,VERTICAL	$786,329.43	4	$3,145,317.72	2	0	0	0	0	2	0
	4	2012_10	10	7	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	0	0	3	0	3	0
		2012_11	11	8	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	0	0	3	0	3	0
		2012_12	12	9	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	0	0	3	0	3	0
2013	1	2013_1	1	10	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	3	0	0	0	3	0
		2013_2	2	11	015251263	STABILIZER,VERTICAL	$749,864.65	2	$1,499,729.30	0	1	0	0	0	1	0
		2013_3	3	12	015251263	STABILIZER,VERTICAL	$749,864.65	3	$2,249,593.95	0	2	0	0	0	2	0
	2	2013_4	4	1	015251263	STABILIZER,VERTICAL	$749,864.65	1	$749,864.65	0	1	0	0	0	1	0
		2013_5	5	2	015251263	STABILIZER,VERTICAL	$749,864.65	6	$4,499,187.90	0	3	0	0	0	3	0
		2013_6	6	3	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	2	0	0	0	2	0
	3	2013_7	7	4	015251263	STABILIZER,VERTICAL	$749,864.65	1	$749,864.65	0	1	0	0	0	1	0
		2013_8	8	5	015251263	STABILIZER,VERTICAL	$749,864.65	3	$2,249,593.95	0	2	0	0	0	2	0
		2013_9	9	6	015251263	STABILIZER,VERTICAL	$749,864.65	4	$2,999,458.60	0	2	0	0	0	2	0
	4	2013_10	10	7	015251263	STABILIZER,VERTICAL	$782,639.44	5	$3,913,197.20	0	2	0	0	0	2	0
		2013_11	11	8	015251263	STABILIZER,VERTICAL	$782,639.44	4	$3,130,557.76	0	2	0	0	0	2	0
		2013_12	12	9	015251263	STABILIZER,VERTICAL	$782,639.44	16	$12,522,231.04	0	7	0	0	0	7	0
2014	1	2014_3	3	12	015251263	STABILIZER,VERTICAL	$782,639.44	9	$7,043,754.96	0	3	0	0	0	3	0
	2	2014_5	5	2	015251263	STABILIZER,VERTICAL	$782,639.44	1	$782,639.44	0	0	0	1	0	1	0

Figure 70. NIIN 01-525-1263 Monthly Demand, Admin Lead Time and Production Lead Time

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APPENDIX B. LEAD-TIME DEMAND FORECASTS FOR THE NIIN 011707951 TURBINE ROTOR BLADE

Information found in this section regarding product demand forecast for the turbine rotor blade:

A. Statistical analysis of product demand

B. Observations from the statistical analysis

C. Lead-time-demand forecast: an input for inventory policy

D. Inventory-policy formulation

E. Conditional value at risk analysis

A. STATISTICAL ANALYSIS OF PRODUCT DEMAND

The graph in Figure 71 spans four fiscal years and the trend appears to be a gradual decrease in demand. Figure 72 supports the assumption that demand is decreasing during each fiscal year in the model (see the mean values). If the trend continues, the decrease in demand during FY14 could be significant, over 20% [(430–330)/430 = 23%]. Observe that the graph in Figure 73 presenting demand from the two most recent fiscal years, reveals a decrease in demand from FY 12 to FY 13 of approximately 5.5% [(455–430)/455 = 5.5%].

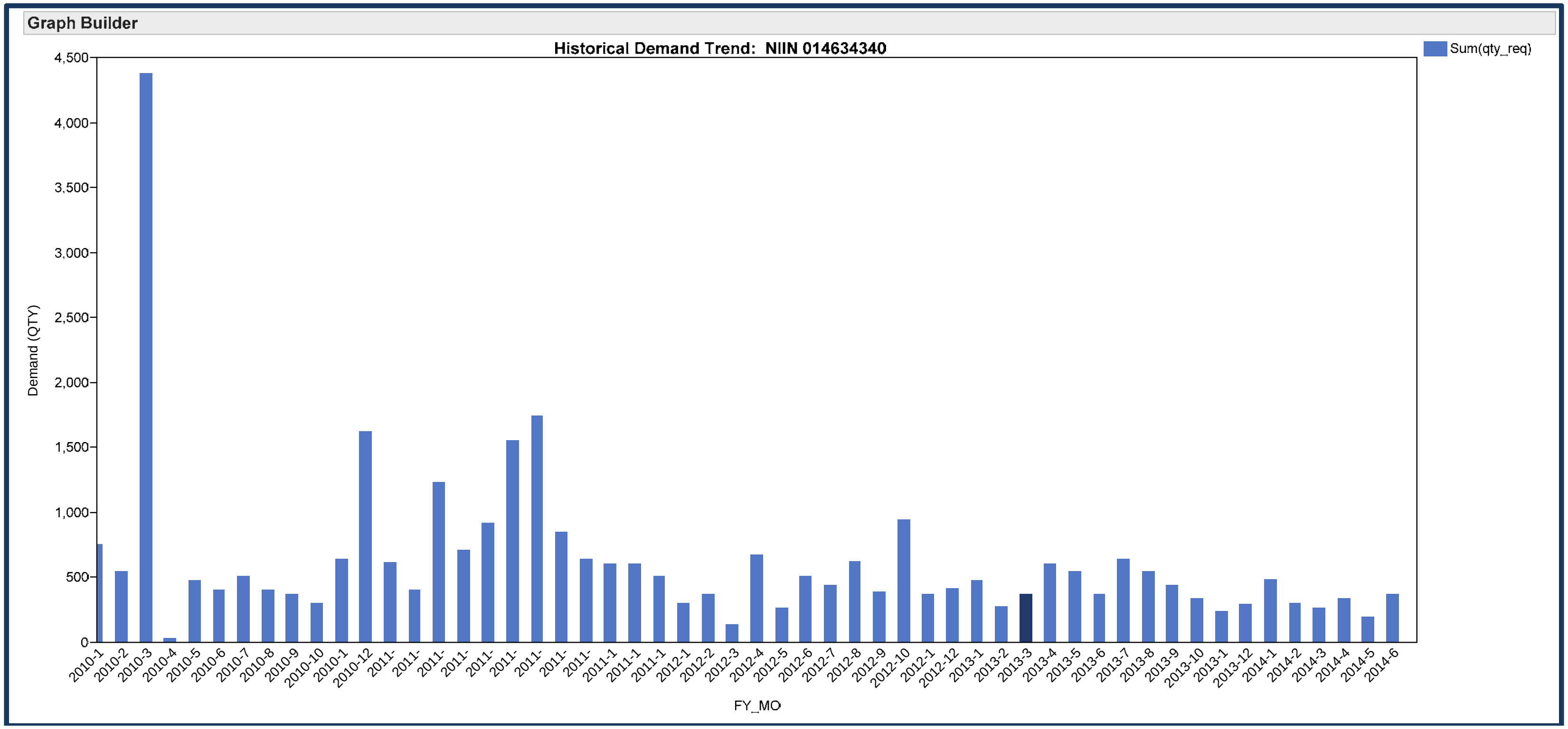


Figure 71. NIIN 01-463-4340 Four Fiscal Year Demand Trend

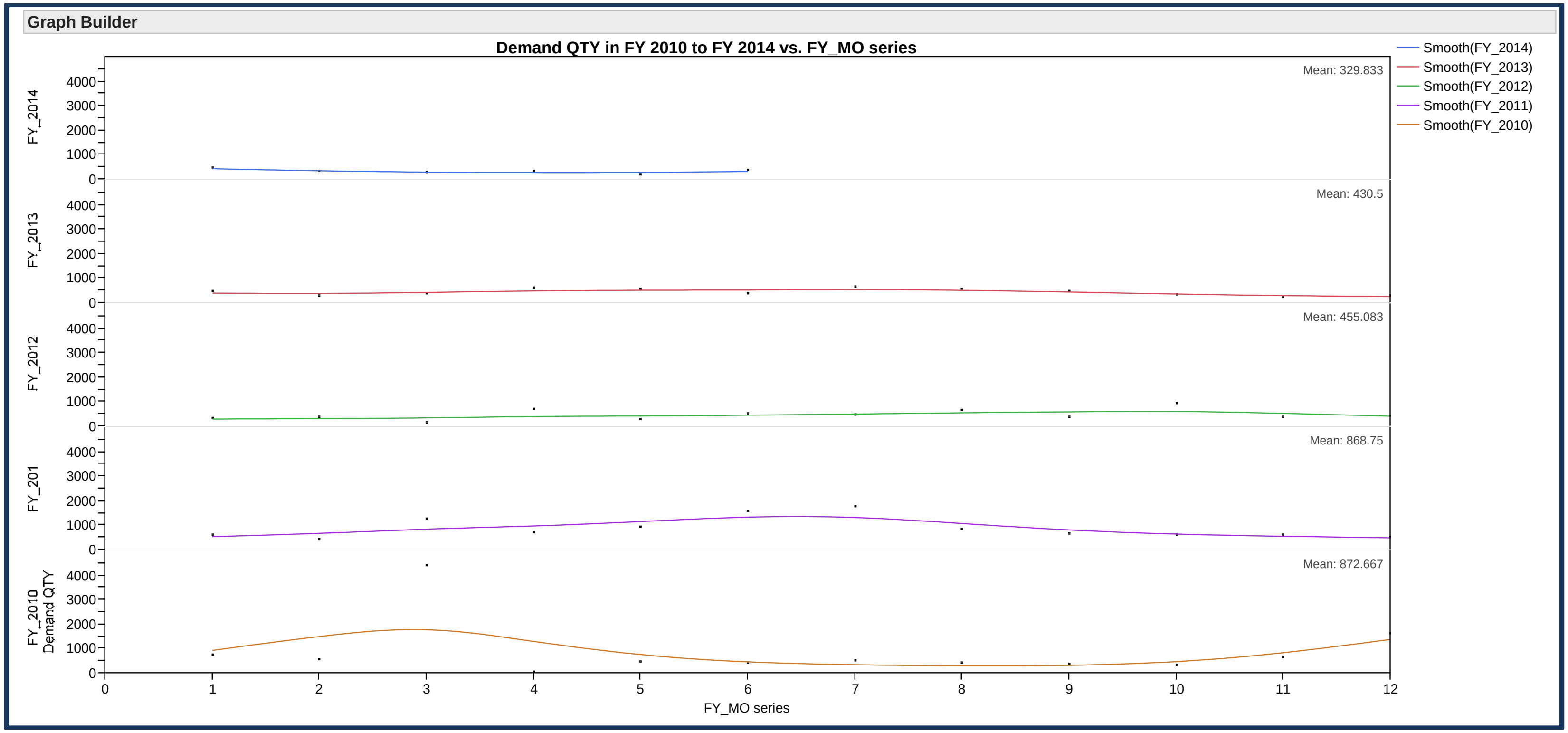


Figure 72. NIIN 01-463-4340 Monthly Demand FY 10 to FY 14

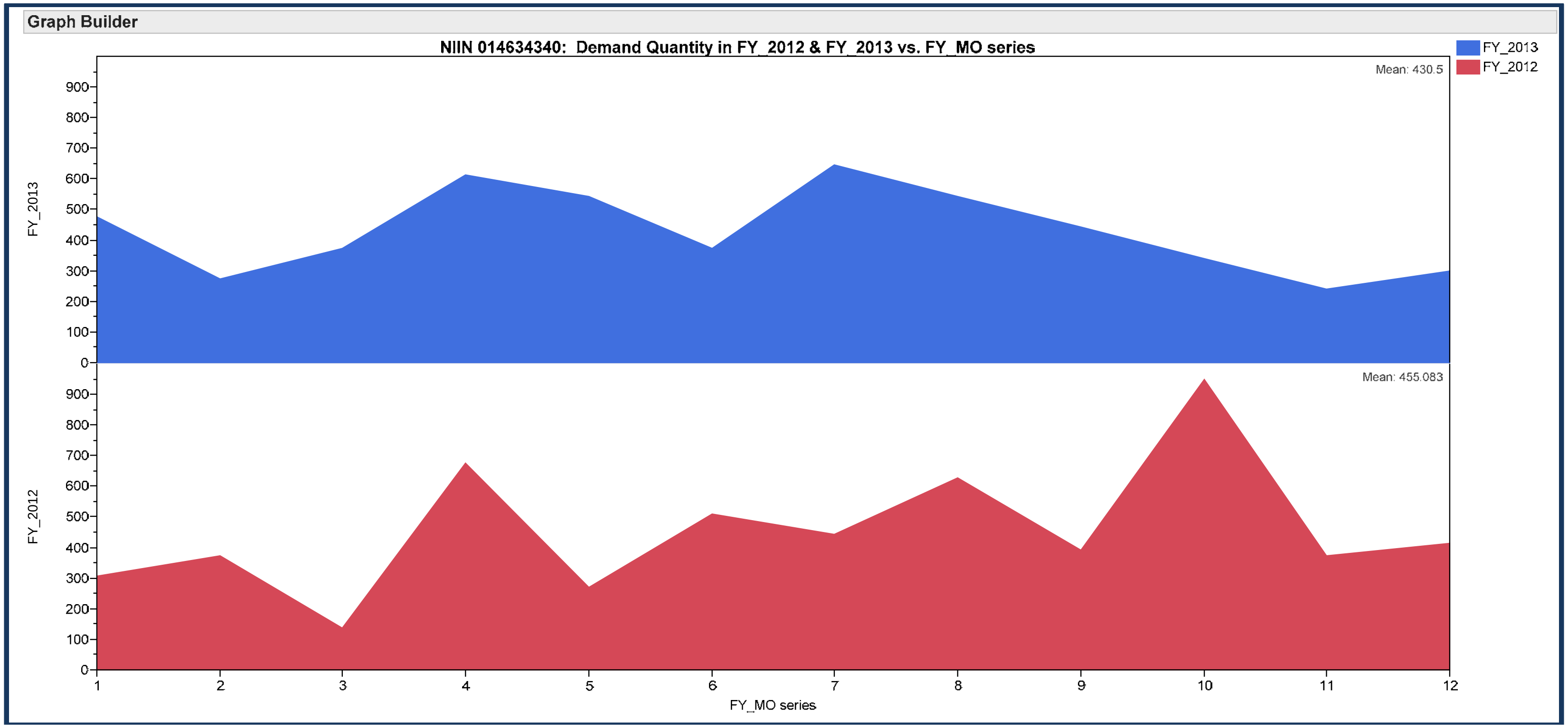


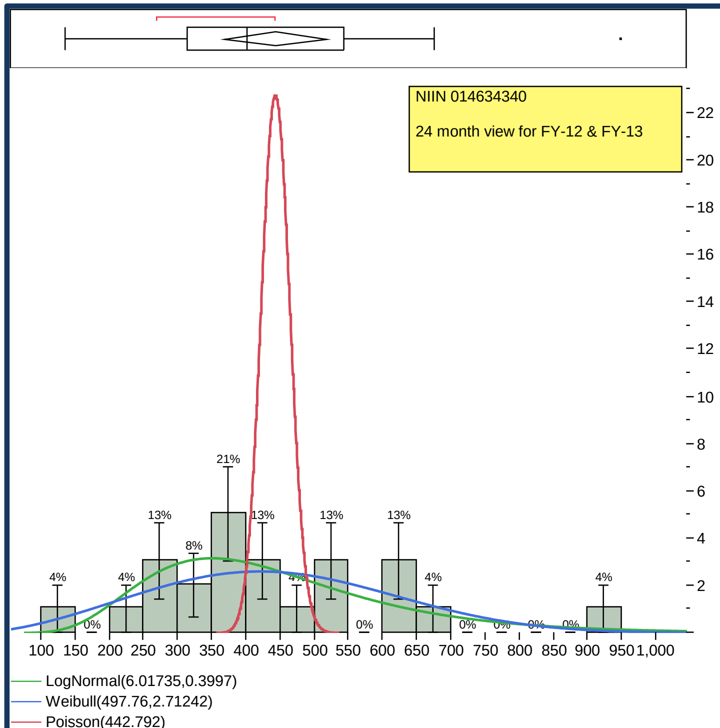
Figure 73. NIIN 01-463-4340 Demand Graph FY 12 and FY 13

- **Probability Distribution of Demand, FY 12 and FY 13**

Figure 74 shows an outlier value in July 2012 (FY_MO = 10). The outlier quantity is 948 units and causes a disproportionately large increase in the mean value of demand (noise or high, unpredictable variability).

Note the confidence intervals section (in the red square). The lower confidence level of the mean (μ) value is 369 units. As discussed above, a downtrend dominates the overall pattern of product demand; therefore the lower confidence level of the mean (369 units) could be a valid parameter value for a forecast model. The takeaway is that the lower confidence value of the mean, 369 units, will be used as a variable in the forecast model.

Figure 75 shows that we replaced the outlier value in July 2012 (948 units) with a previous fiscal year value (September 2011 = 510 units). This change caused a decrease in the mean (μ) value from 443 to 425, as well as a decrease in the standard deviation from 175 to 139. This is illustrated in Figure 75 and tabulated in Figure 76 as prediction intervals.



Quantiles

100.0%	maximum	948
99.5%		948
97.5%		948
90.0%		661
75.0%	quartile	544
50.0%	median	401.5
25.0%	quartile	314.5
10.0%		255.5
2.5%		136
0.5%		136
0.0%	minimum	136

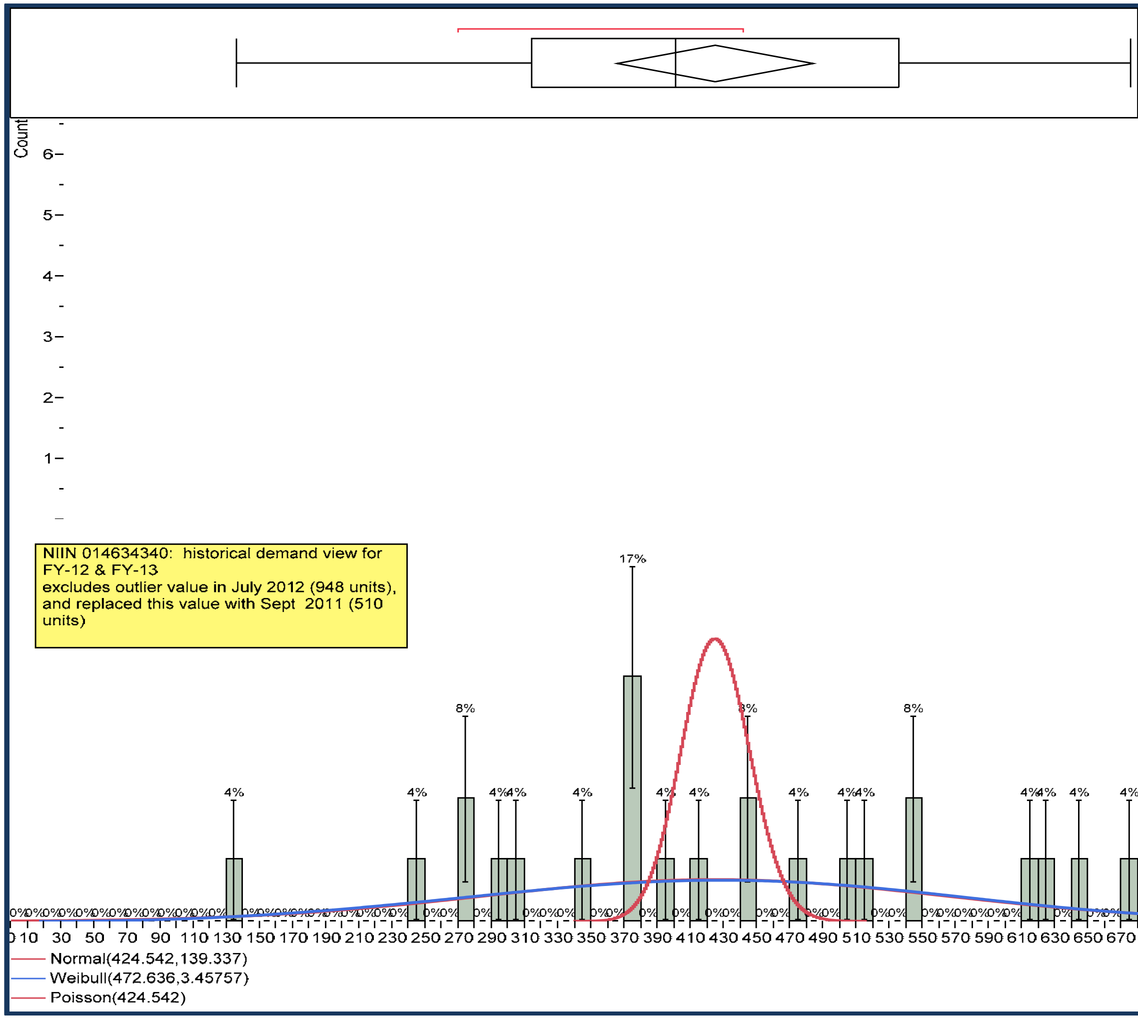
Summary Statistics

Mean	442.79167
Std Dev	175.10915
Std Err Mean	35.744006
Upper 95% Mean	516.73378
Lower 95% Mean	368.84956
N	24
Sum	10,627
Variance	30663.216
Skewness	0.9559327
Kurtosis	1.681371
Median	401.5
Mode	374
Range	812
Interquartile Range	229.5

Confidence Intervals

Parameter	Estimate	Lower CI	Upper CI	1-Alpha
Mean	442.7917	368.8496	516.7338	0.950
Std Dev	175.1092	136.0972	245.6362	0.950

Figure 74. NIIN 01-463-4340 Demand Data Histogram FY 12 and FY 13



Quantiles

100.0%	maximum	676
99.5%		676
97.5%		676
90.0%		636
75.0%	quartile	535.5
50.0%	median	401.5
25.0%	quartile	314.5
10.0%		255.5
2.5%		136
0.5%		136
0.0%	minimum	136

Summary Statistics

Mean	424.54167
Std Dev	139.33724
Std Err Mean	28.442096
Upper 95% Mean	483.37862
Lower 95% Mean	365.70471
N	24
Sum	10,189
Variance	19414.868
Skewness	0.0730598
Kurtosis	-0.516824
Median	401.5
Mode	374
Range	540
Interquartile Range	221

Figure 75. NIIN 01-463-4340 Demand Fit Histogram Excluding Outlier Value

Confidence Intervals

Parameter	Estimate	Lower CI	Upper CI	1-Alpha
Mean	424.5417	365.7047	483.3786	0.950
Std Dev	139.3372	108.2948	195.4568	0.950

Prediction Interval

Parameter	Future N	Lower PI	Upper PI	1-Alpha
Individual	9	-10.5455	859.6289	0.950
Mean	9	311.8775	537.2059	0.950
Std Dev	9	70.03149	233.4757	0.950

Compare Distributions

Show	Distribution	Number of Parameters	-2*LogLikelihood	AICc
☑	Weibull	2	303.729665	308.301093
☐	Extreme Value	2	303.729665	308.301093
☑	Normal	2	304.080116	308.651544
☐	Gamma	2	305.083046	309.654474
☐	Johnson Sl	3	304.02799	311.22799
☐	LogNormal	2	307.079125	311.650554
☐	Johnson Su	4	304.02799	314.133253
☐	GLog	3	307.079125	314.279125
☐	Normal 2 Mixture	5	301.32049	314.653824
☐	Normal 3 Mixture	8	304.631188	330.231188
☐	Exponential	1	338.448487	340.630306

Figure 76. NIIN 01-463-4340 Prediction Intervals

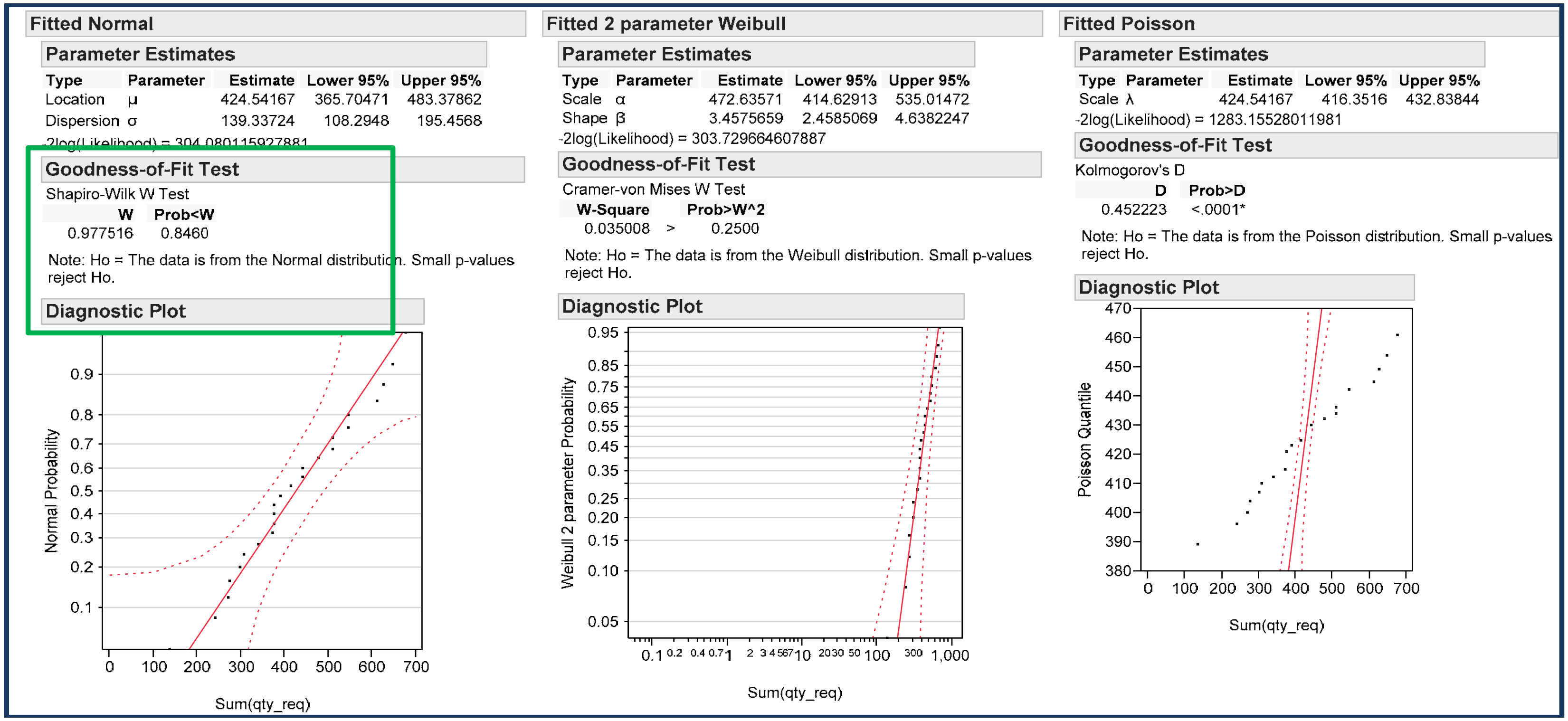


Figure 77. NIIN 01-463-4340 Goodness-Of-Fit Tests

Notice that the “diagnostic plot” in the fitted normal distribution (green box in Figure 77) shows the normal distribution curve has the best probability distribution fit found (.846). Chapter II discusses the relationship between a high p-value and distribution goodness of fit. Takeaway: The normal distribution will be used in the forecast model.

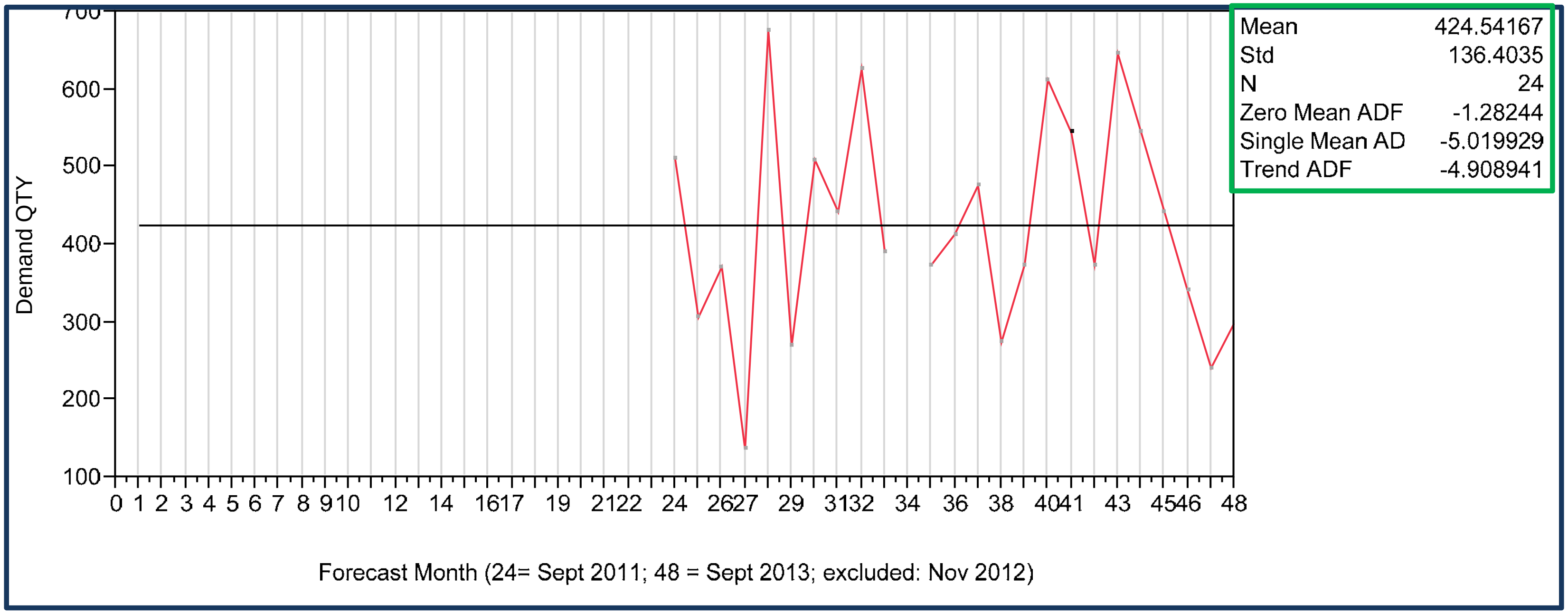
- ***Time-series Forecasts Sensitivity Analysis***

The time-series forecast in Figure 78 uses a 24 month time segment (FY12 to FY13) for the forecast model.

Product demand during each fiscal year is highly variable (see the standard deviation value). However, the mean value and standard deviation are the strongest indicators of what demand quantity could be during the lead-time demand (demand between replenishment cycles).

Compare the section above prediction interval highlighted in the green square, and the time-series graph section below in the green square. Both the mean values and the standard deviation are significantly different. The prediction-interval section shows a lower confidence mean value of 311 (and standard deviation of 70), whereas the time-series section shows a mean value of 424 (and standard deviation of 136).

Takeaway*:* Since a downtrend dominates the overall pattern of product demand, we will conduct a Monte Carlo forecast simulation using a normal distribution with a mean value of 311 and standard deviation of 70.



Report	Graph	Model	DF	Variance	AIC	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
☑	☐	Seasonal Exponential Smoothing(12, Zero to One)	8	14670.769	135.23552	135.84069	-0.58	131.23552	0.675588		30.022084	131.58243
☑	☐	Winters Method (Additive)	7	17755.202	136.70266	137.61041	-0.52	130.70266	0.324412		29.359080	128.42120
☑	☑	Simple Exponential Smoothing(Zero to One)	21	22033.049	286.45250	287.54354	-0.25	284.4525	0.000000		34.439092	123.65214
☑	☐	Damped-Trend Linear Exponential Smoothing	19	24352.359	290.45250	293.72563	-0.25	284.4525	0.000000		34.439092	123.65214

Figure 78. NIIN 01-463-4340 Simple Exponential Smoothing Forecast

Figures 79, 80, and 81depict the range in exponential smoothing forecasts

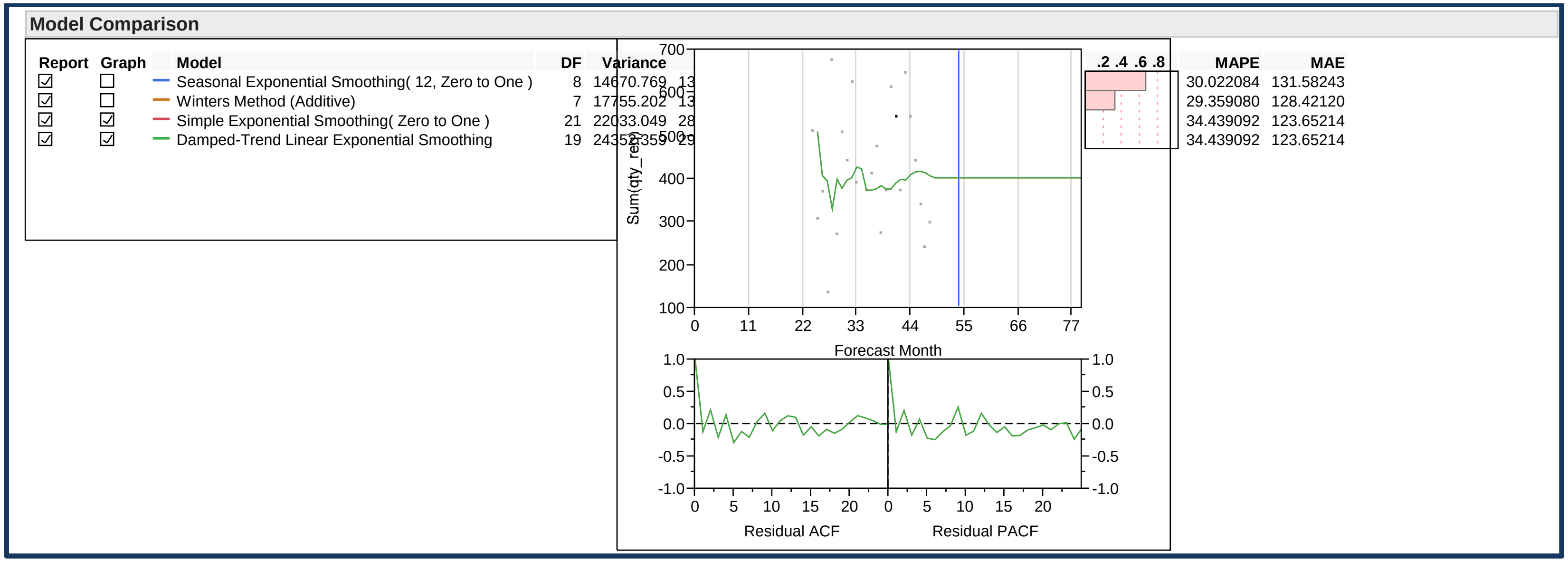


Figure 79. NIIN 01-463-4340 Combined Forecast Simple Exponential Smoothing and Damped-Trend Linear Exponential Smoothing Forecasts

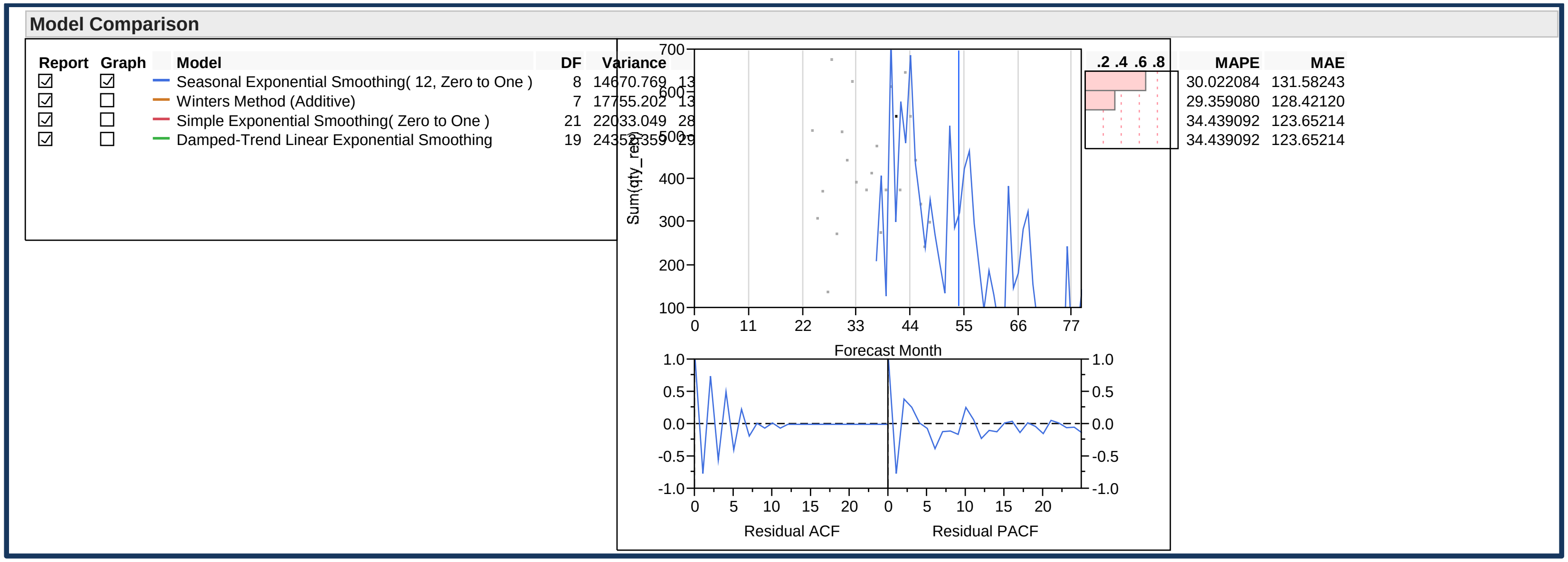


Figure 80. NIIN 01-463-4340 Seasonal Exponential Smoothing Forecast

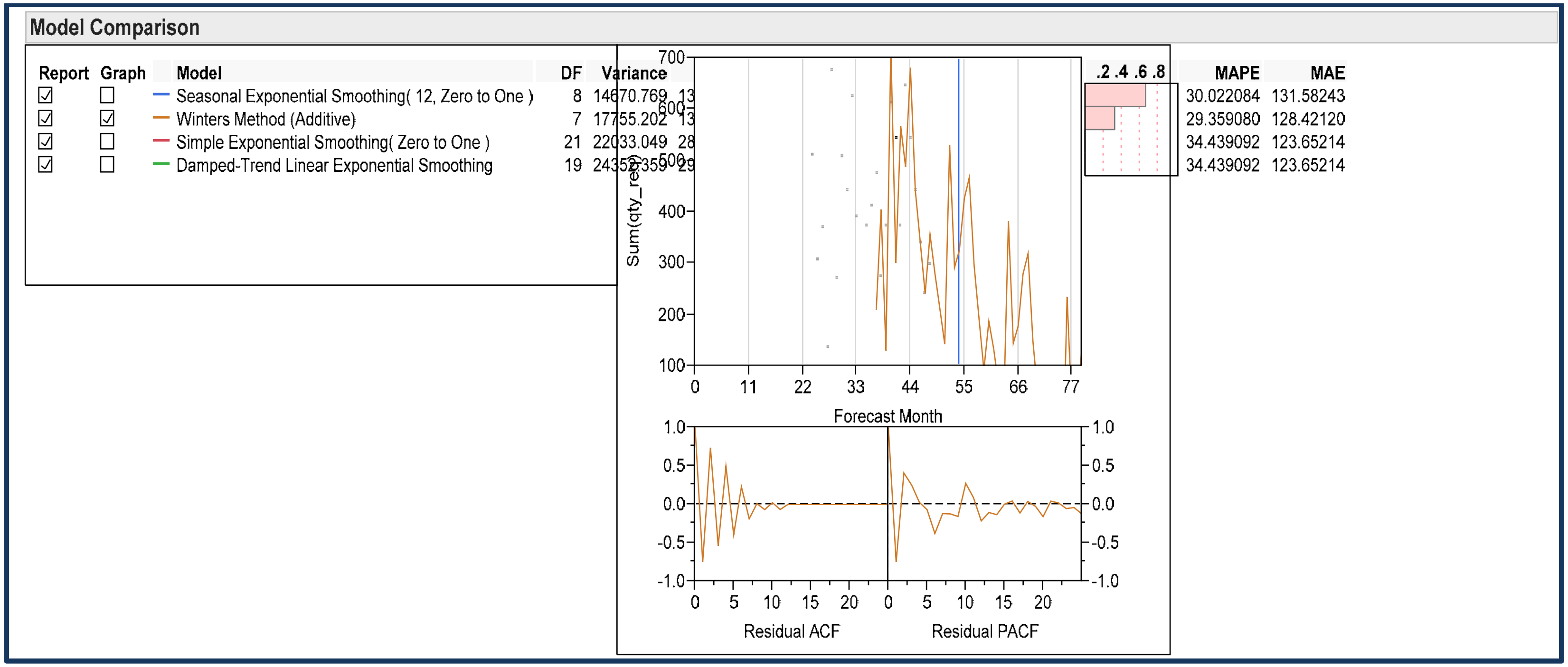


Figure 81. NIIN 01-463-4340, Winter’s Method Forecast

B. OBSERVATIONS FROM THE STATISTICAL ANALYSIS

JMP statistical analysis shows that the demand for this NIIN appeared non-static and highly variable. Although no adequate probability distribution fit was found, the normal distribution had the best goodness of fit (highest p-value for a distribution fit).

Crystal Ball's Monte Carlo simulation: Crystal Ball found no adequate distribution fit for the historical demand data. Therefore, a Monte Carlo simulation will be run using the normal distribution with a mean of 311 and standard deviation of 70.

C. LEAD-TIME DEMAND FORECAST (NINE MONTHS)

- **First forecast**

We assume this set of forecasts was conducted at the end of FY13. We used a two- month window from FY12 to FY13 and excluded one outlier value in July 2012 (910 units). The dominant pattern was marked by slowing demand across succeeding fiscal years; therefore, we used the parameters found in the prediction-interval section of the univariate analysis. These parameters were the lowest among the predictive values available from the normal distribution univariate analysis section.

- Normal distribution parameters for the Crystal Ball forecast model: mean (μ) = 311 and standard deviation (σ) = 70.
- Lead-time demand during nine months = 2,799 units.
- 95% fill rate = lead-time demand + safety stock = 3,145 units

The Monte Carlo simulations in figures 82, 83 and 84 provide various forecasts from 9-months (lead time), 12-months (fiscal year 2014) and 6-months (to gauge forecast model performance against the actual FY14 demand). Actual demand data for October 2013 to March 2014 was known. Therefore, we used the 6-month forecast to gauge performance (forecast error between the model and the real world).

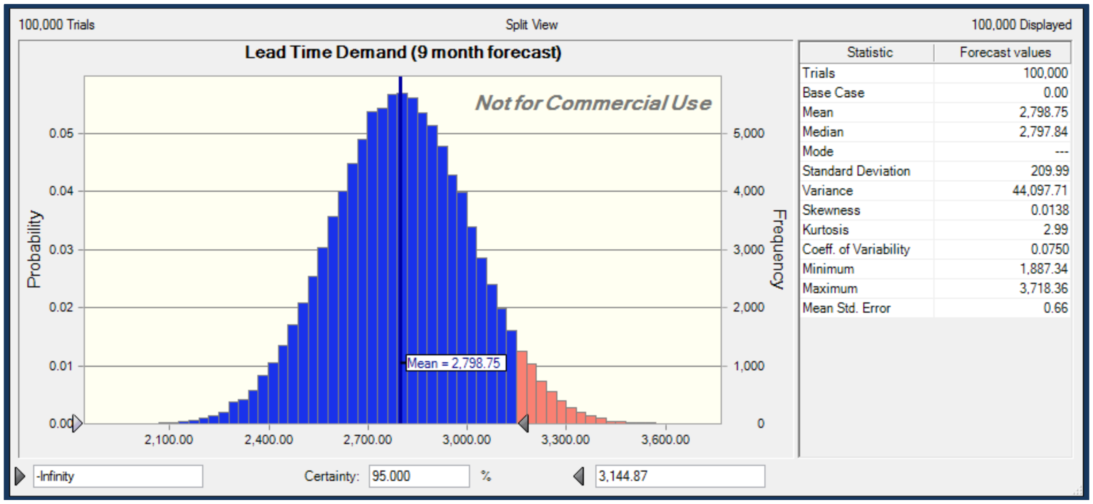


Figure 82. NIIN 01-463-4340 9-Month Forecast Simulation

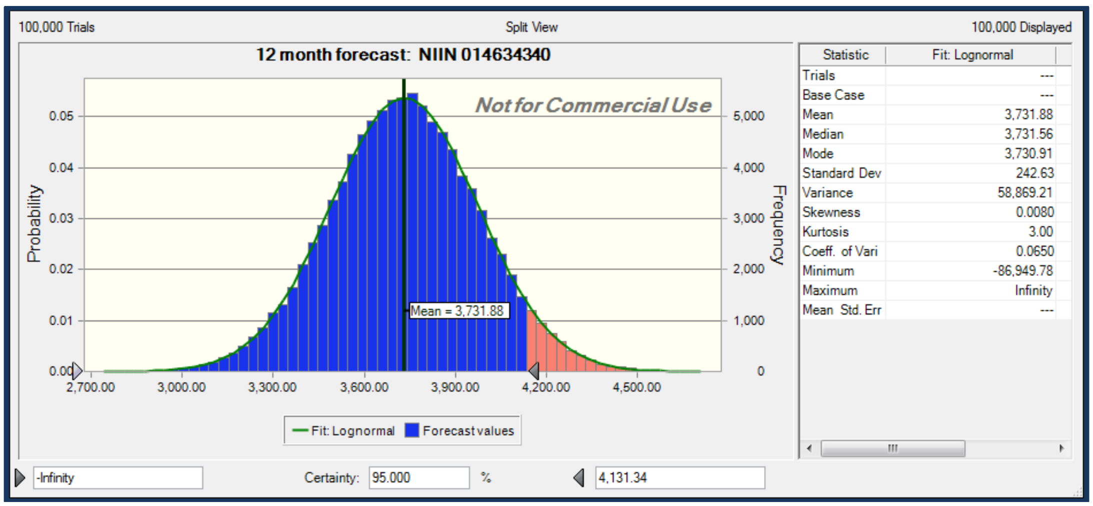


Figure 83. NIIN 01-463-4340 12-Month Forecast Simulation

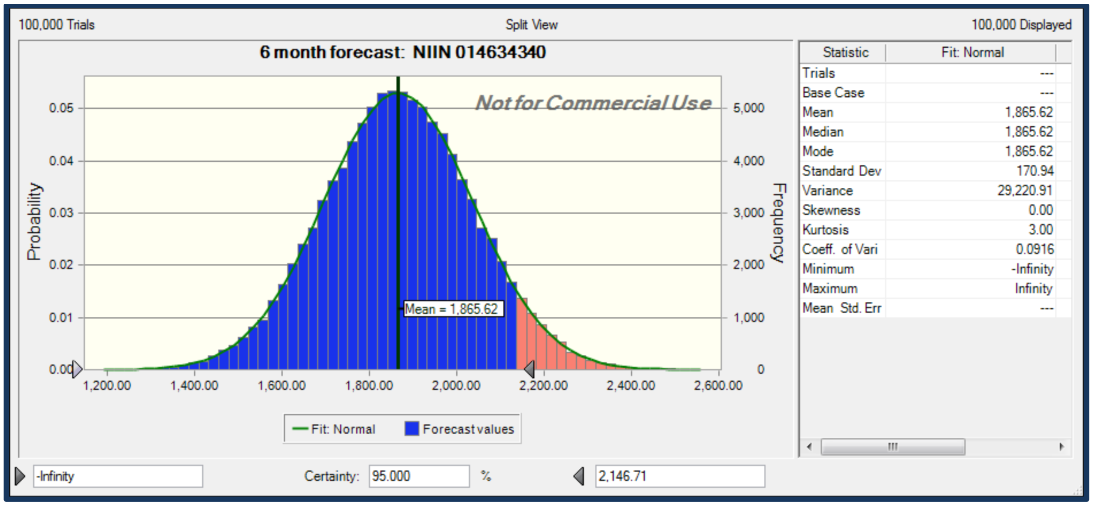


Figure 84. NIIN 01-463-4340 6-Month Forecast Simulation

- **Observations from the first forecast**

It is assumed the observations from the first forecast were compiled after a 6 month lapse, at the end of March 2014. The graph in Figure 85 shows the forecast error = 6%. If this forecast was used to formulate inventory policy, DLA would realize an inventory cost reduction, because actual inventory is high (see paragraph 4, inventory policy formulation).

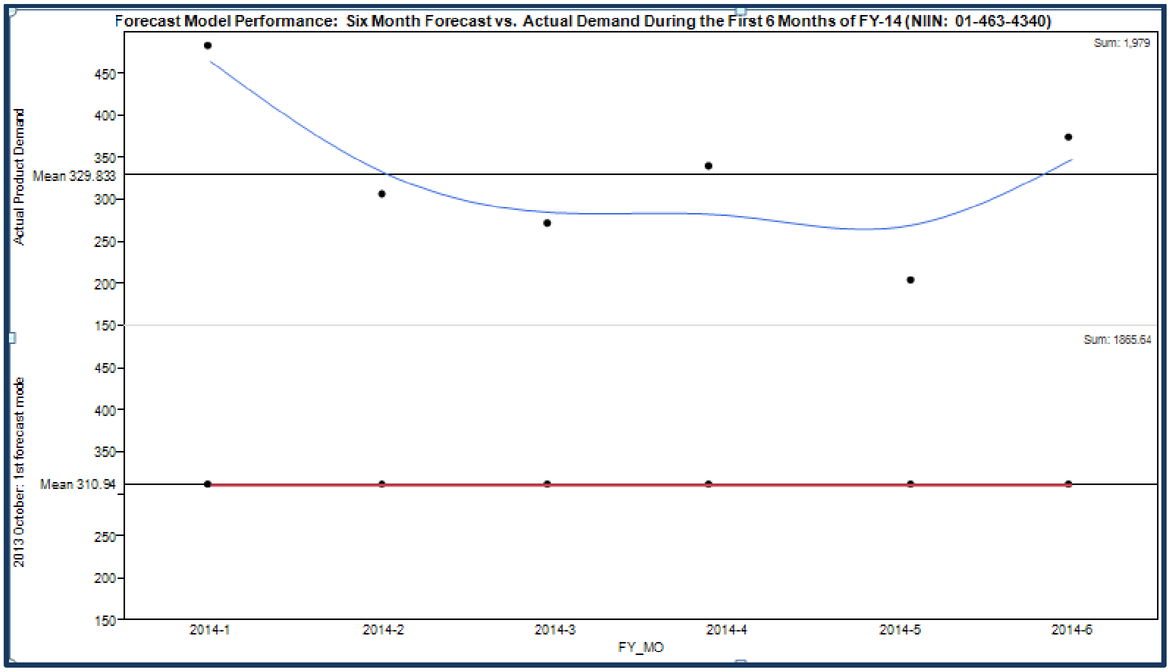


Figure 85. NIIN 01-463-4340 Monte Carlo Forecast Model versus Actual FY 14 Demand

Table 21 compares the results of the first forecast against actual product demand during the first six months of FY14. The lead-time demand forecast is also provided (shaded gray). Notice the forecast reorder point is 3,145 units.

Six Month Forecast: Comparison of the forecast model vs. actual demand

FY_MO	Actual Product Demand	Average Forecast: 1st model	Average Forecast: 2nd model
2014-1	483	310.94	
2014-2	306	310.94	
2014-3	272	310.94	
2014-4	340	310.94	
2014-5	204	310.94	
2014-6	374	310.94	
Total	**1979**	**1865.62**	**0**
		Oct. 2013 six month forecast error:	
Delta forecast #1	113.38	ABS(1979-1866)/1979 = 6%	Apr. 2014 six month forecast error:

All forecasts:		
FY 2014, six months:	1,866	
FY 2014, twelve months:	3,732	
Lead Time demand, 9 months:	*2,799*	
Reorder Point:	3,145	

The market for this product is non-static, characterized by shifting conditions.

Table 21. NIIN 01-463-4340 Comparison First Forecast versus Actual Demand

- **Second Forecast**

For this research, a second forecast would normally be run and we would assume it was conducted on the first week of April 2014 (mid-year forecast). However, a second forecast simulation was not conducted, due to the high accuracy of the first forecast model.

D. INVENTORY-POLICY FORMULATION: AS CONDITIONS CHANGE, SO MUST INVENTORY POLICY

The results of the Monte Carlo simulations provide guidance for inventory-policy change. Whereas DLA inventory policy for FY14 set the reorder point at 12,414 units, the October 2013 forecast called for a reorder point of 3,145 units. As shown in Table 22, that is a difference of 9,269. At a FY14 price of about $4,648 per unit, the inventory cost reduction would be about $43 million (with selling price is used in lieu of cost).

Evolving Inventory Policy: Narrowing the gap beween the model and the real world			
	Actual DLA QTY	1st forecast	**2nd forecast**
Effective date:	**FY 14**	Oct-13	**Apr-14**
Forecast		2,799	**0**
Safety Stock:	**1,590**	346	**0**
Reorder Point:	**12,414**	3,145	**0**
The market for this product is non-static, characterized by shifting conditions and uncertainty. The Apr-14 forecast used 6 months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.			
FY-14 unit price	Delta	**cost savings**	**cost increase**
$4,648	9,269	**$43,081,570**	

Table 22. NIIN 01-463-4340 Comparison Second Forecast versus Actual Demand

- **Inventory-Management Assumption**

Since this NIIN is a class-A item, it should be managed with a continuous inventory policy, due to this product's impact on (potential) overall annual revenue.

JMP software training (online) provides the insight, "All models are wrong, but some are useful… The illustration below Figure 86 states that the organization's performance is a function of their learning curve." See how this statement applies to

inventory policy formulation in the next section as it discusses the cost reduction benefit of reducing lead time.

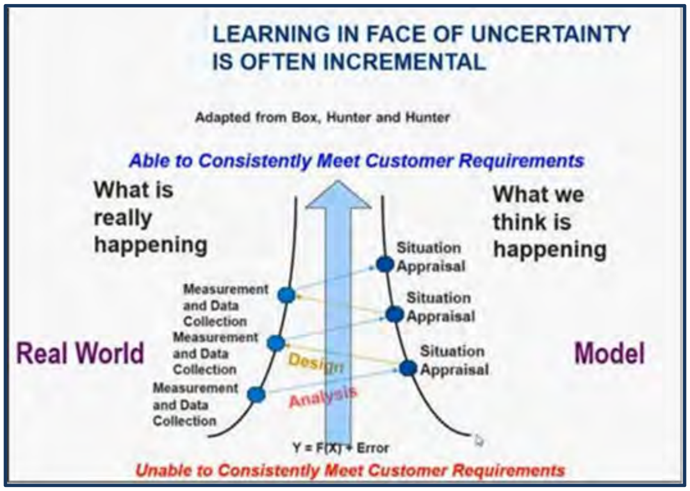


Figure 86. Learning curve, adopted from Exploring Best Practices in Design of Experiments SAS Institute (Webinar 2014)

E. CONDITIONAL-VALUE-AT-RISK ANALYSIS

The graph in Figure 87 shows the lead-time demand forecast. The 95% fill rate is shaded in blue and the value of this area under the demand curve is 3,145 units. The remaining 5% is the conditional value at risk (the right tail of the distribution curve). Figure 88 represents the range of values of the conditional value at risk. The conclusions from the Monte Carlo simulation above are summarized in Table 23.

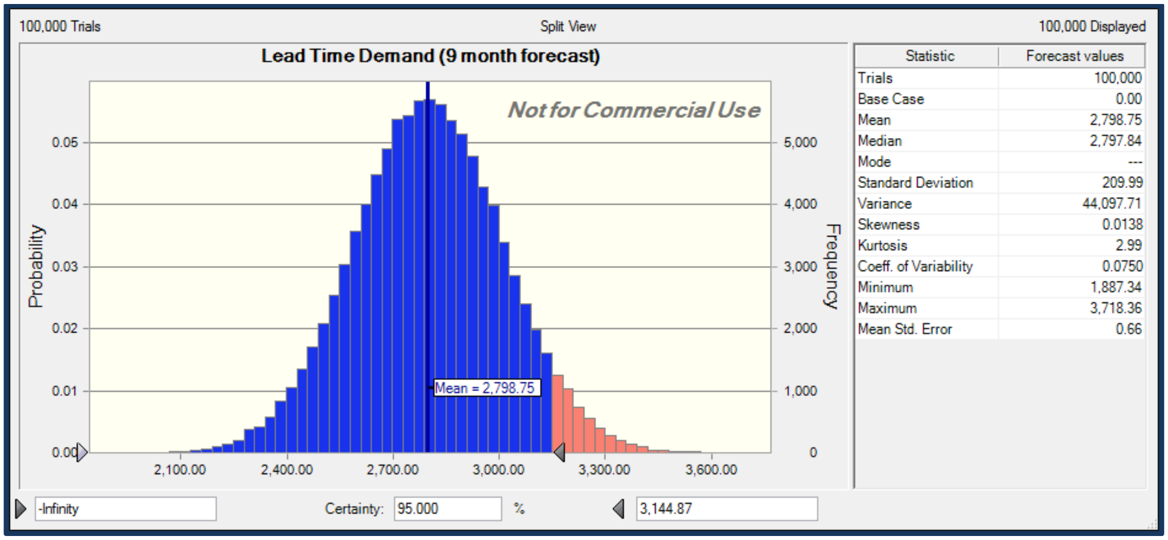


Figure 87. NIIN 01-463-4340 9-Month Lead Time Demand Forecast

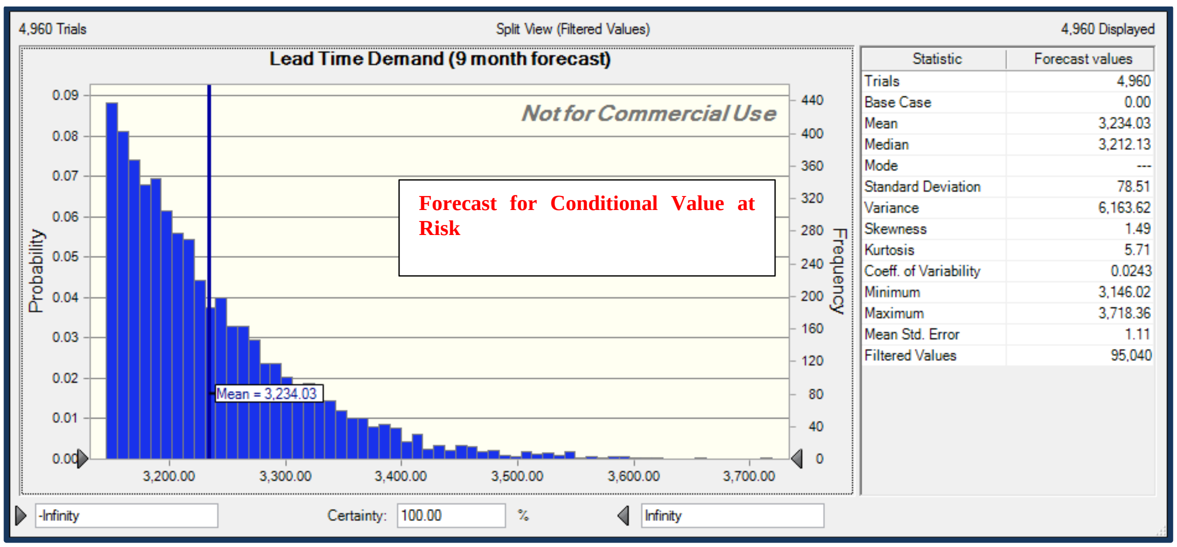


Figure 88. NIIN 01-463-4340 Conditional Value at Risk

The average lead-time demand forecast (50% probability	**2,799 units** (lead time = 11 months)
A 95% fill rate quantity equals	**3,145 units** of inventory
Conditional risk: If demand exceeds stock on hand during the replenishment cycle, the expected shortage is	**89 units** (see forecast right tail distribution: 3,234 – 3,145 = 89)
How bad can things get if there is a stock out? The maximum shortage forecasted is	**574 units** (3,719 – 3,145 = 574)

Table 23. NIIN 01-463-4340 Lead Time Demand Forecast and Stock out Risk Analysis Summary Table

- **Improving the Organization's Learning Curve**

The organization should produce demand forecasts and risk analysis for this NIIN on a quarterly basis at least and adjust the inventory policy (reorder point and safety stock levels) as required. This implies integrated planning with the contracting officer and item manager for negotiating the right procurement contract with the supplier.

- **Learning-Curve Potential**

Table 24 and Figure 89 below illustrates that lead time for this NIIN shifts annually. Further reducing the replenishment lead time (admin + procurement) would reduce the exposure period of demand uncertainty and likely lead to a lower safety stock and reorder point, thus lowering inventory costs.

Lead Time (FY-14)	**NIIN 01-463-4340**
procurement lead time days:	180
admin lead time days:	90
total days:	270
months	**9**

Table 24. NIIN 01-463-4340 Admin and Procurement Lead Time.

NIIN 014634340: Tabulate of Demand from FY 2010 to FY 2014

							qty_req	Revenue	alt			plt			
FY	Quarter	FY_MO series	FY_QTR	niin	itm_name	std_u_price	Sum	Sum	15	30	90	173	180	388	389
2010	1	1	2010-1	014634340	BLADE,TURBINE ROTOR	1,086.53	760	$825,763	0	8	0	0	0	0	8
		2	2010-1	014634340	BLADE,TURBINE ROTOR	1,086.53	546	$593,245	0	9	0	0	0	0	9
		3	2010-1	014634340	BLADE,TURBINE ROTOR	1,086.53	4,379	$4,757,915	0	14	0	0	0	0	14
	2	4	2010-2	014634340	BLADE,TURBINE ROTOR	1,086.53	34	$36,942	0	1	0	1	0	0	0
		5	2010-2	014634340	BLADE,TURBINE ROTOR	1,086.53	476	$517,188	0	7	0	7	0	0	0
		6	2010-2	014634340	BLADE,TURBINE ROTOR	1,086.53	408	$443,304	0	9	0	9	0	0	0
	3	7	2010-3	014634340	BLADE,TURBINE ROTOR	1,086.53	510	$554,130	0	13	0	13	0	0	0
		8	2010-3	014634340	BLADE,TURBINE ROTOR	1,086.53	408	$443,304	0	11	0	11	0	0	0
		9	2010-3	014634340	BLADE,TURBINE ROTOR	1,086.53	371	$403,103	0	8	0	8	0	0	0
	4	10	2010-4	014634340	BLADE,TURBINE ROTOR	1,136.62	306	$347,806	0	7	0	0	0	7	0
		11	2010-4	014634340	BLADE,TURBINE ROTOR	1,136.62	646	$734,257	0	13	0	0	0	13	0
		12	2010-4	014634340	BLADE,TURBINE ROTOR	1,136.62	1,628	$1,850,417	0	13	0	0	0	13	0
2011	1	1	2011-1	014634340	BLADE,TURBINE ROTOR	1,136.62	619	$703,568	0	14	0	0	0	14	0
		2	2011-1	014634340	BLADE,TURBINE ROTOR	1,136.62	408	$463,741	0	9	0	0	0	9	0
		3	2011-1	014634340	BLADE,TURBINE ROTOR	1,136.62	1,234	$1,402,589	0	12	0	0	0	12	0
	2	4	2011-2	014634340	BLADE,TURBINE ROTOR	1,136.62	712	$809,273	0	11	0	0	0	11	0
		5	2011-2	014634340	BLADE,TURBINE ROTOR	1,136.62	918	$1,043,417	0	12	0	0	0	12	0
		6	2011-2	014634340	BLADE,TURBINE ROTOR	1,136.62	1,557	$1,769,717	0	16	0	0	0	16	0
	3	7	2011-3	014634340	BLADE,TURBINE ROTOR	1,136.62	1,747	$1,985,675	0	13	0	0	0	13	0
		8	2011-3	014634340	BLADE,TURBINE ROTOR	1,136.62	850	$966,127	0	15	0	0	0	15	0
		9	2011-3	014634340	BLADE,TURBINE ROTOR	1,136.62	646	$734,257	0	14	0	0	0	14	0
	4	10	2011-4	014634340	BLADE,TURBINE ROTOR	1,111.19	612	$680,048	0	12	0	0	0	12	0
		11	2011-4	014634340	BLADE,TURBINE ROTOR	1,111.19	612	$680,048	0	10	0	0	0	10	0
		12	2011-4	014634340	BLADE,TURBINE ROTOR	1,111.19	510	$566,707	0	8	0	0	0	8	0
2012	1	1	2012-1	014634340	BLADE,TURBINE ROTOR	4,551.8	306	$1,392,851	0	5	0	0	5	0	0
		2	2012-1	014634340	BLADE,TURBINE ROTOR	4,551.8	371	$1,688,718	0	4	0	0	4	0	0
		3	2012-1	014634340	BLADE,TURBINE ROTOR	4,551.8	136	$619,045	0	3	0	0	3	0	0
	2	4	2012-2	014634340	BLADE,TURBINE ROTOR	4,551.8	676	$3,077,017	9	0	0	0	9	0	0
		5	2012-2	014634340	BLADE,TURBINE ROTOR	4,551.8	270	$1,228,986	4	0	0	0	4	0	0
		6	2012-2	014634340	BLADE,TURBINE ROTOR	4,551.8	509	$2,316,866	8	0	0	0	8	0	0
	3	7	2012-3	014634340	BLADE,TURBINE ROTOR	4,551.8	442	$2,011,896	8	0	0	0	8	0	0
		8	2012-3	014634340	BLADE,TURBINE ROTOR	4,551.8	626	$2,849,427	11	0	0	0	11	0	0
		9	2012-3	014634340	BLADE,TURBINE ROTOR	4,551.8	390	$1,775,202	7	0	0	0	7	0	0
	4	10	2012-4	014634340	BLADE,TURBINE ROTOR	4,106.39	948	$3,892,858	0	0	11	0	11	0	0
		11	2012-4	014634340	BLADE,TURBINE ROTOR	4,106.39	374	$1,535,790	0	0	6	0	6	0	0
		12	2012-4	014634340	BLADE,TURBINE ROTOR	4,106.39	413	$1,695,939	0	0	9	0	9	0	0
2013	1	1	2013-1	014634340	BLADE,TURBINE ROTOR	4,106.39	476	$1,954,642	0	0	8	0	8	0	0
		2	2013-1	014634340	BLADE,TURBINE ROTOR	4,106.39	274	$1,125,151	0	0	7	0	7	0	0
		3	2013-1	014634340	BLADE,TURBINE ROTOR	4,106.39	374	$1,535,790	0	0	8	0	8	0	0
	2	4	2013-2	014634340	BLADE,TURBINE ROTOR	4,106.39	612	$2,513,111	0	0	10	0	10	0	0
		5	2013-2	014634340	BLADE,TURBINE ROTOR	4,106.39	544	$2,233,876	0	0	9	0	9	0	0
		6	2013-2	014634340	BLADE,TURBINE ROTOR	4,106.39	374	$1,535,790	0	0	8	0	8	0	0
	3	7	2013-3	014634340	BLADE,TURBINE ROTOR	4,106.39	646	$2,652,728	0	0	12	0	12	0	0
		8	2013-3	014634340	BLADE,TURBINE ROTOR	4,106.39	544	$2,233,876	0	0	13	0	13	0	0
		9	2013-3	014634340	BLADE,TURBINE ROTOR	4,106.39	442	$1,815,024	0	0	9	0	9	0	0
	4	10	2013-4	014634340	BLADE,TURBINE ROTOR	4,647.92	340	$1,580,293	0	0	7	0	7	0	0
		11	2013-4	014634340	BLADE,TURBINE ROTOR	4,647.92	241	$1,120,149	0	0	7	0	7	0	0
		12	2013-4	014634340	BLADE,TURBINE ROTOR	4,647.92	299	$1,389,728	0	0	10	0	10	0	0
2014	1	1	2014-1	014634340	BLADE,TURBINE ROTOR	4,647.92	483	$2,244,945	0	0	13	0	13	0	0
		2	2014-1	014634340	BLADE,TURBINE ROTOR	4,647.92	306	$1,422,264	0	0	8	0	8	0	0
		3	2014-1	014634340	BLADE,TURBINE ROTOR	4,647.92	272	$1,264,234	0	0	8	0	8	0	0
	2	4	2014-2	014634340	BLADE,TURBINE ROTOR	4,647.92	340	$1,580,293	0	0	10	0	10	0	0
		5	2014-2	014634340	BLADE,TURBINE ROTOR	4,647.92	204	$948,176	0	0	4	0	4	0	0
		6	2014-2	014634340	BLADE,TURBINE ROTOR	4,647.92	374	$1,738,322	0	0	7	0	7	0	0

Figure 89. NIIN 01-463-4340 Monthly Demand, Admin Lead Time and Production Lead Time

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APPENDIX C. LEAD-TIME DEMAND FORECASTS FOR THE NIIN 011707951 THERMOCOUPLE, CONTRACT, AND ENGINE

Information found in this section regarding product demand forecast for the thermocouple, contact, and engine includes:

A. Statistical analysis of product demand

B. Observations from the statistical analysis

C. Lead-time-demand forecast: an input for inventory policy

D. Inventory Policy Formulation

E. Conditional value at risk analysis

A. STATISTICAL ANALYSIS OF PRODUCT DEMAND

The demand for this product was non-static and highly variable from FY10 to FY13. Note the outlier value in January 2013 (fiscal year month 2013–2014), as shown in Figure 90. A look at this NIIN as shown in Figure 91 indicates the high variability of demand associated with this product. The graph in Figure 92 is a view of product demand without the January 2013 outlier value. Note the decrease in mean value from 2,067 to 1,978.

The two graphs in figures 93 and 94 show a trend of decreased mean demand across fiscal years. This information is useful for drafting a forecast model for FY14 product demand.

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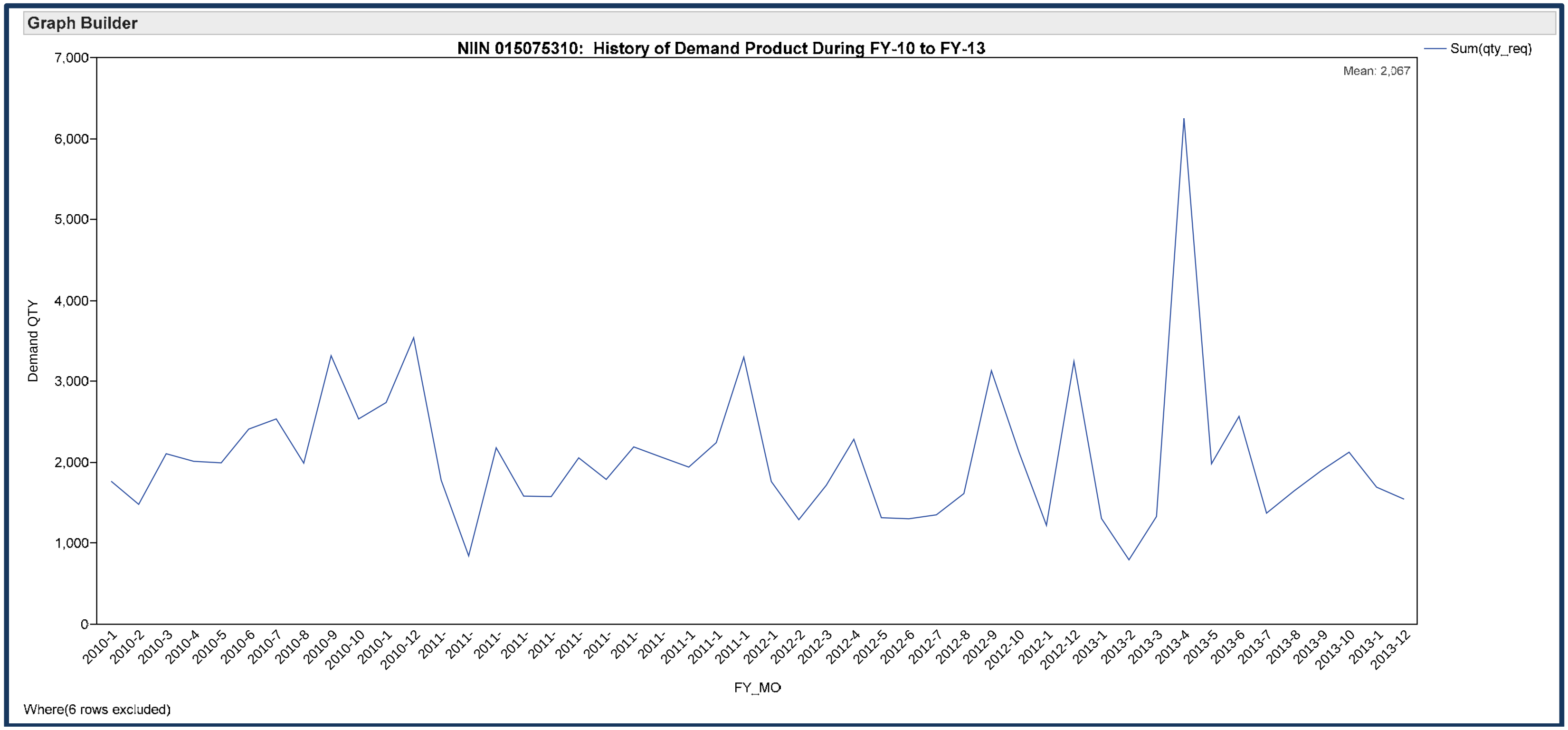

Figure 90. NIIN 01-507-5310 Monthly Demand FY10 - FY13

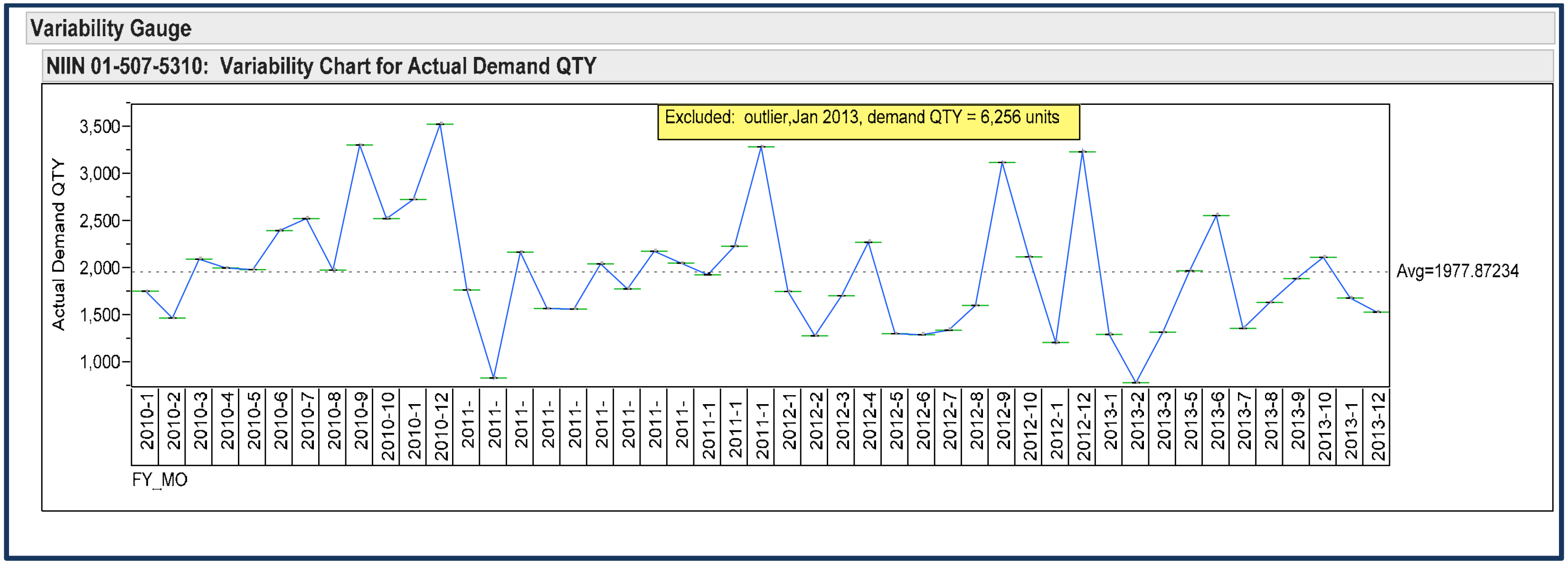

Figure 91. NIIN 01-507-5310 Variability in Monthly Demand

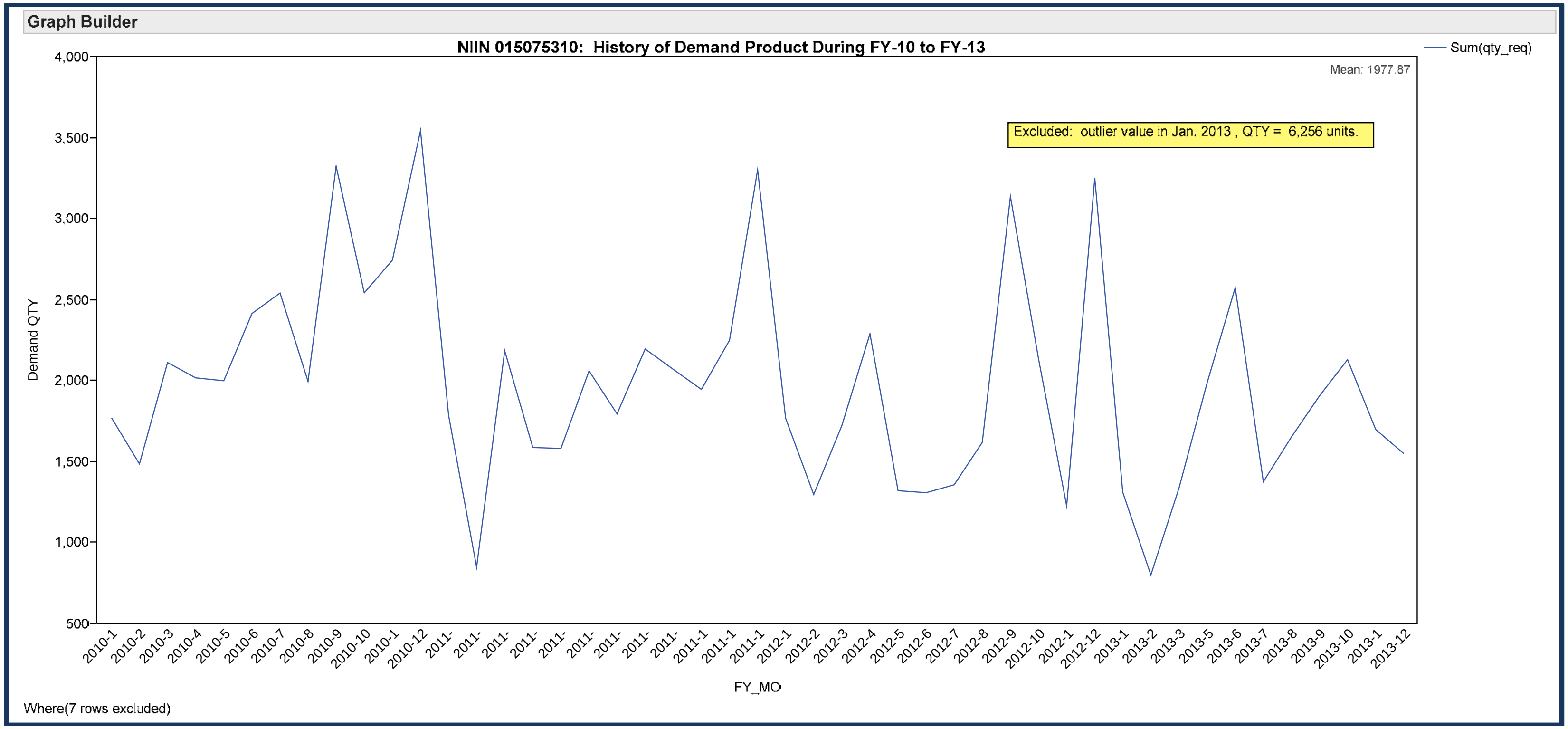

Figure 92. NIIN 01-507-5310 Monthly Demand FY10 – FY13 without Outlier

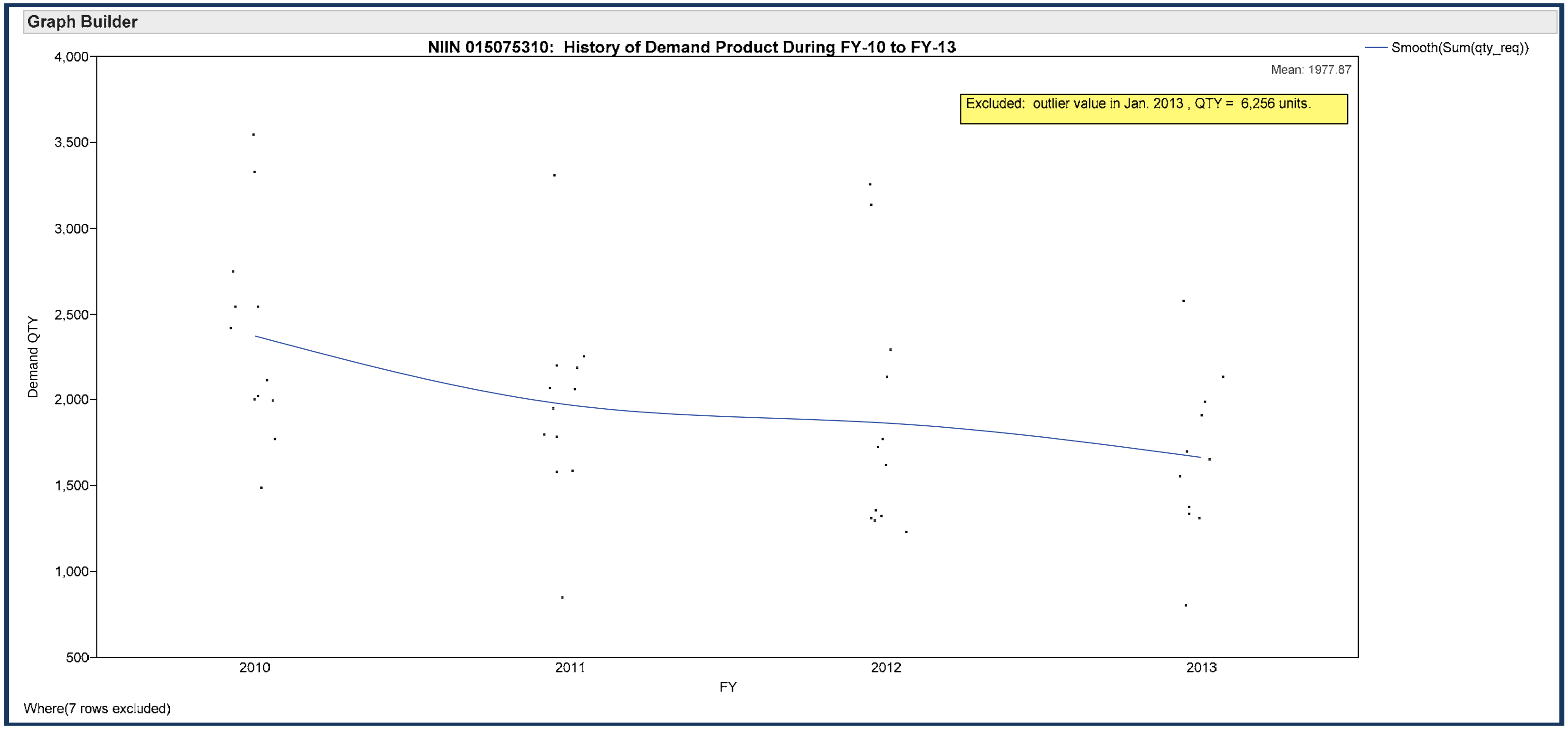

Figure 93. NIIN 01-507-5310 Demand History FY10 – FY13 (A)

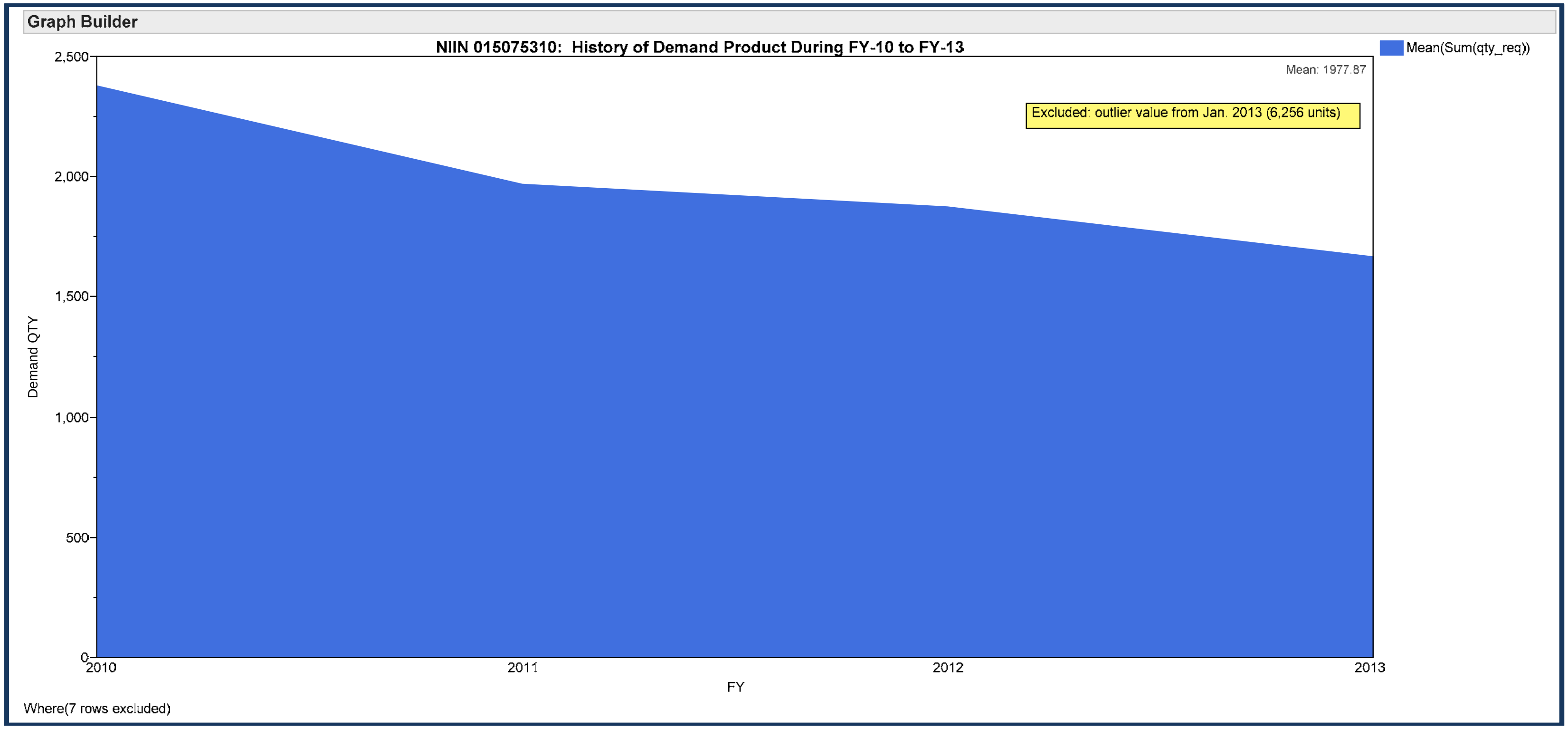

Figure 94. NIIN 01-507-5310 Demand History FY10 – FY13 (B)

- **Probability Distribution Analysis**

In the histogram in Figure 95, the outlier value (QTY = 6,256) is not included; the highest monthly demand value is QTY = 3,546. We are searching for a useful range of values of product demand; therefore, we must avoid using over-inflated values for our forecast model.

Although no adequate distribution fit was found, the LogNormal distribution has the highest p-value.

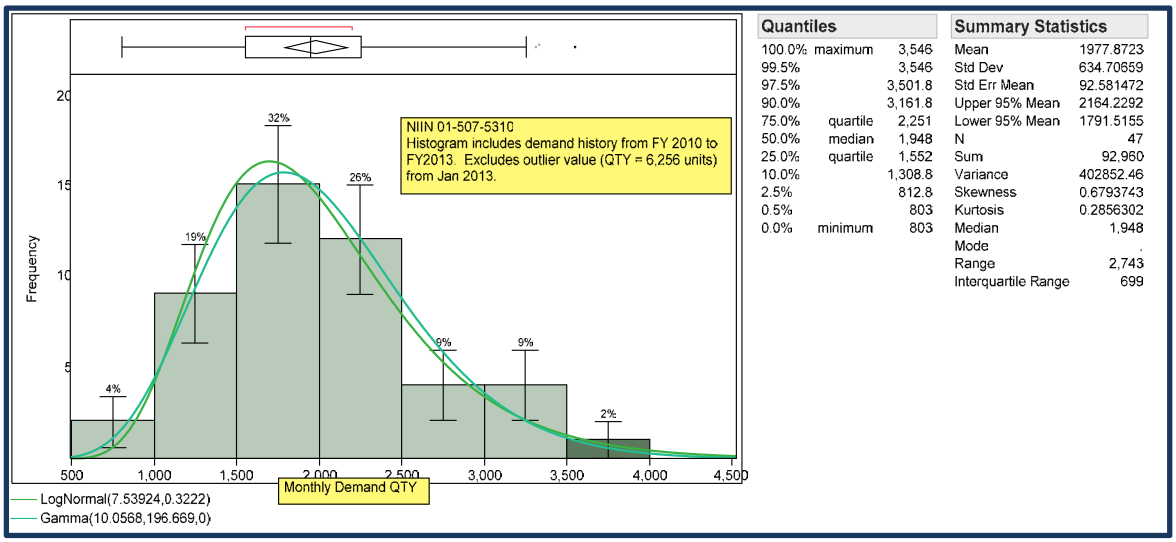

Figure 95. NIIN 01-507-5310 Demand Data Histogram

JMP software used the product demand range from the histogram above to generate the prediction-interval section below in the green box. Notice that the lower–upper ranges in both the mean (μ) value and standard deviation are relatively large. A decreasing trend seems to dominate the pattern of product demand from FY10 to FY13. Therefore, the lower-mean confidence level for monthly demand found in the prediction-interval section in Figure 96 could be the more valid predictor value for our forecast model (μ = 1,424; σ = 256). Normally, the parameters used for a LogNormal function when running a Monte Carlo simulation are given in the “fitted LogNormal” section of

the analysis. However, based on demand pattern, the prediction-interval parameters appear reasonable.

In the "Fitted LogNormal" section in the orange box, the LogNormal P-value is .15; therefore, there is not enough evidence to reject the hypothesis that the demand data does not follow a LogNormal distribution. We will use the parameters (μ = 1,424; σ = 256), in conjunction with the LogNormal distribution. The LogNormal distribution forecast model requires a lower bound value (location); therefore, we will use zero (0) as the low value for monthly product demand.

- **Time-Series Forecasts for Sensitivity Analysis of Demand**

Demand during each fiscal year is highly variable (see the standard deviation value). However, the mean value and standard deviation are the strongest indicators of what demand quantity could be during the lead-time demand (that is, demand between replenishment cycles).

Compare the section in Figure 96 highlighted in the green square, "prediction interval" and the time-series graph in the green square in Figure 97. Both the mean values and the standard deviation are significantly different. The prediction-interval section shows a lower-confidence mean value of 1,424, whereas the time-series section in Figure 100 shows a mean value of 1,978.

Since a gradual decrease seems to dominate the pattern of product demand, we will conduct a Monte Carlo simulation (forecast model) using a LogNormal distribution with parameters: μ = 1,424; σ = 256; location: 0.

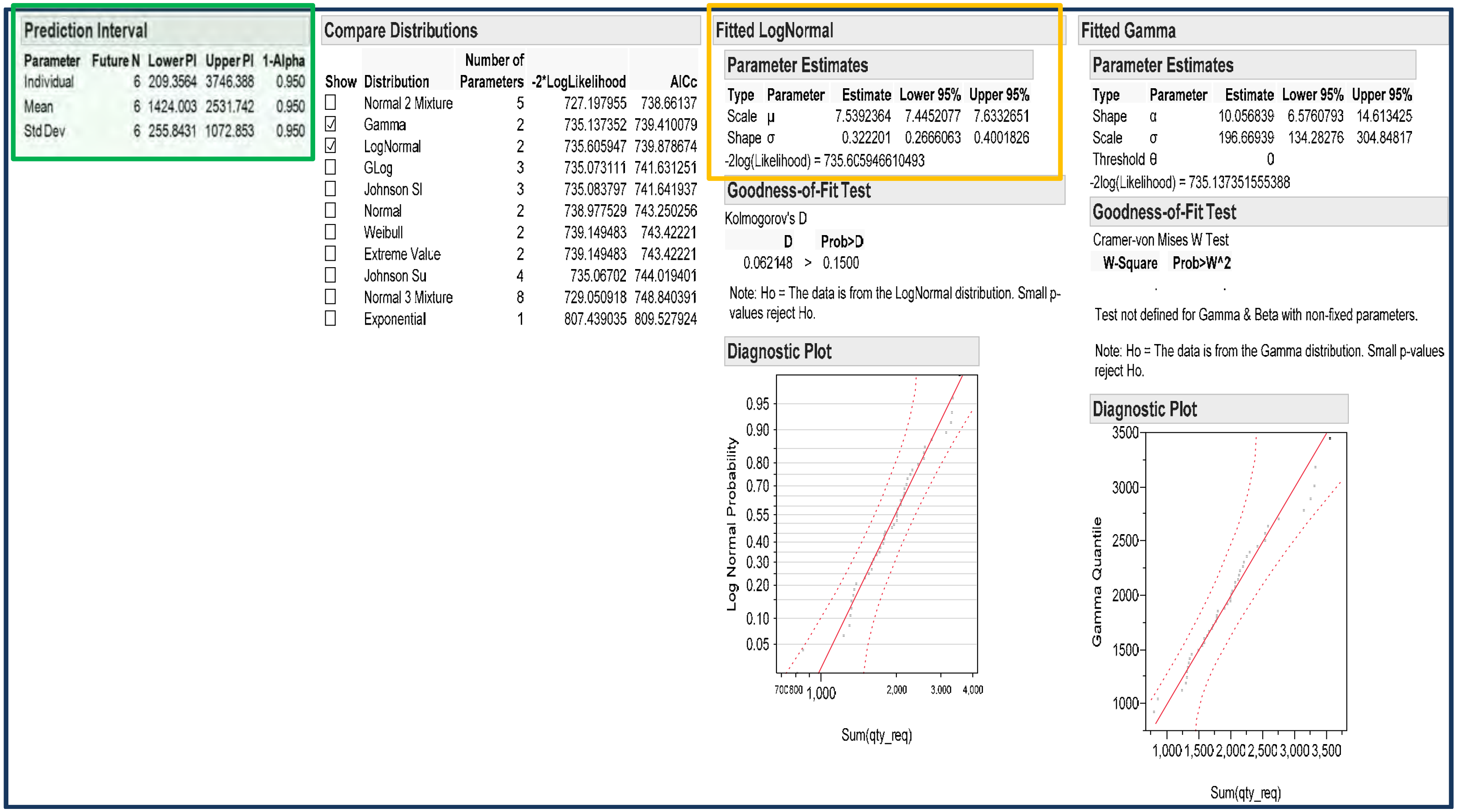

Figure 96. NIIN 01-507-5310 Goodness-Of-Fit Tests (Fitted LogNormal)

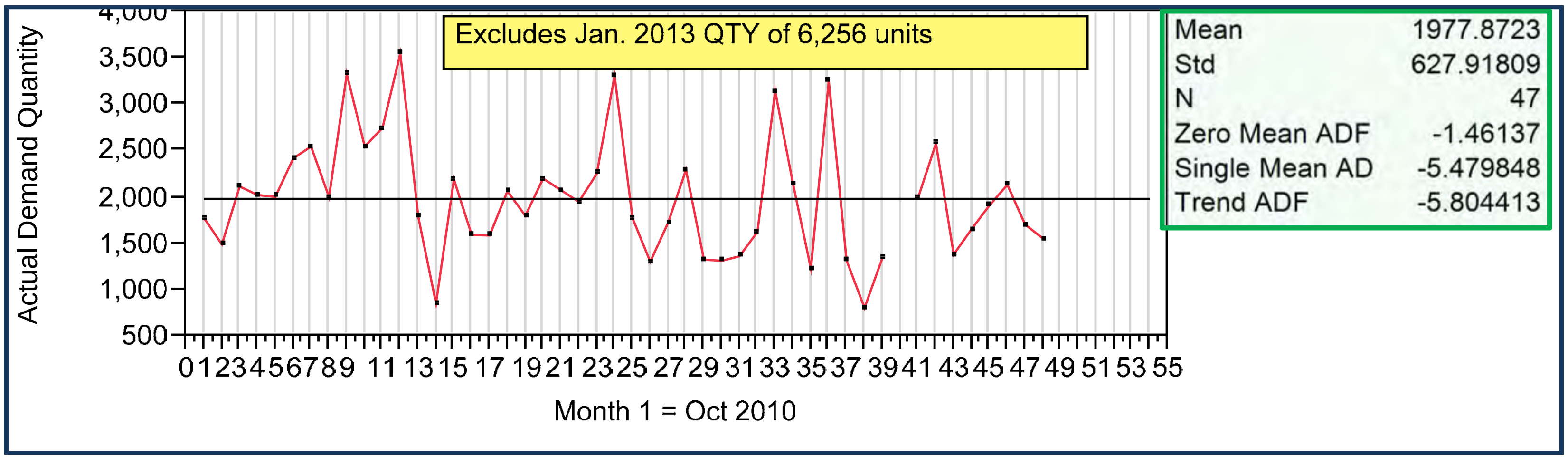

Figure 97. NIIN 01-507-5310 Time Series Prediction Intervals

The JMP time-series analysis produced monthly demand forecasts that hover around a mean value of 1,977; whereas the JMP prediction-interval section generated a lower confidence level of 1,424 . The time-series forecasts might be overinflated, if in fact there is a decrease in demand in FY14. Figures 98 - 101 represent the six-month forecasts for FY14.

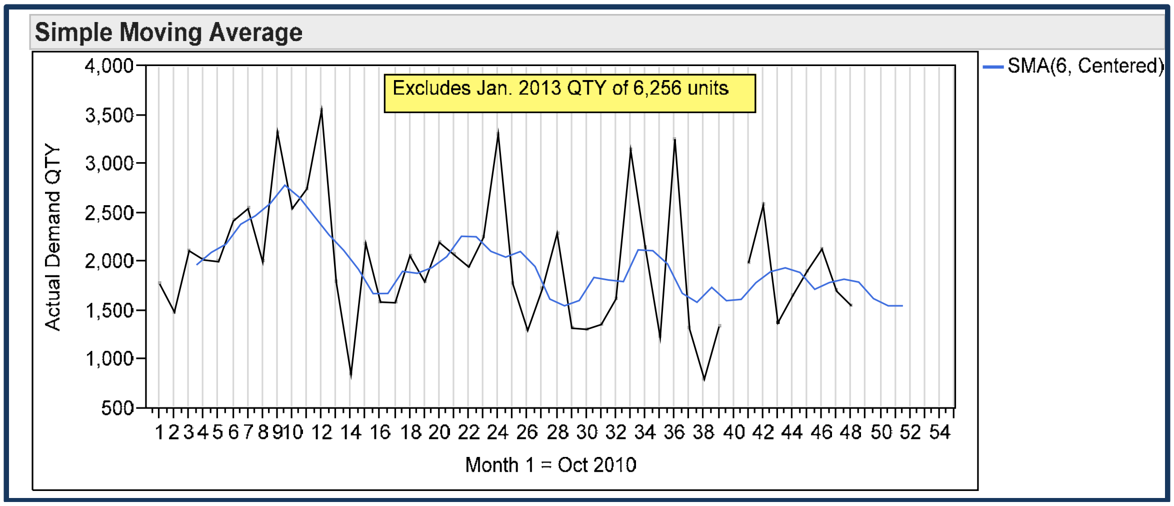

Figure 98. NIIN 01-507-5310 Simple Moving Average Forecast

Model: Simple Exponential Smoothing(Zero to One)

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.08326431	0.0897776	0.93	0.3588

Forecast

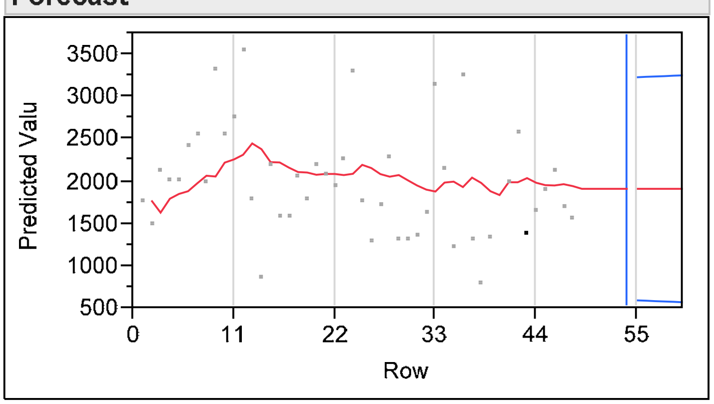

Figure 99. NIIN 01-507-5310 Simple Exponential Smoothing Forecast

Model: Damped-Trend Linear Exponential Smoothing

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.0832643	0.1192834	0.70	0.4890
Trend Smoothing Weight	1.0000000	.	.	.
Damping Smoothing Weight	0.0000000	.	.	.

Forecast

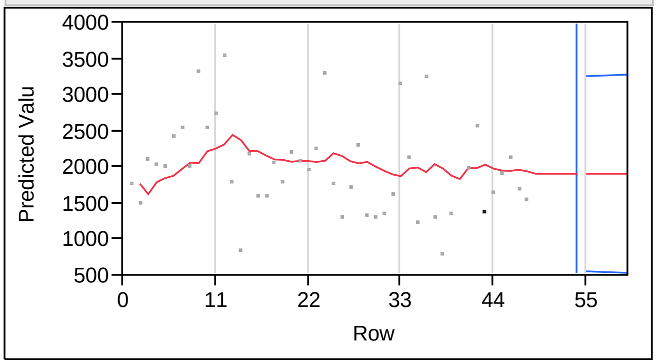

Figure 100. NIIN 01-507-5310 Damped-Trend Linear Exponential Smoothing Forecast

Model: Seasonal Exponential Smoothing(12, Zero to One)

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.35659948	0.1431891	2.49	0.0183*
Seasonal Smoothing Weight	1.7954e-11	0.0000000	.	.

Forecast

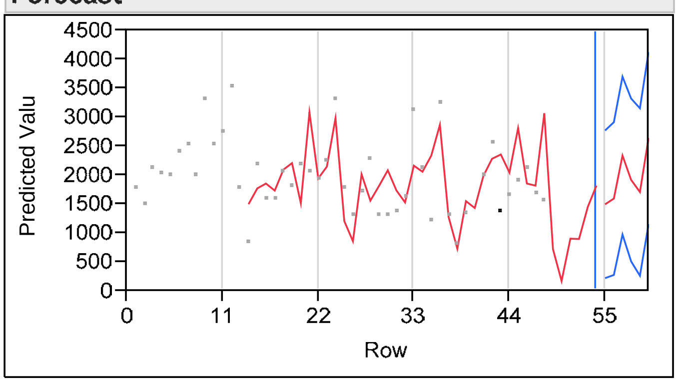

Figure 101. NIIN 01-507-5310 Seasonal Exponential Smoothing

B. OBSERVATIONS FROM THE STATISTICAL ANALYSIS

JMP statistical analysis shows that the demand for this NIIN appeared non-static and highly variable. Although no adequate probability distribution fit was found, the Lognormal distribution had the best goodness of fit (highest p-value for a distribution fit).

C. LEAD-TIME DEMAND FORECAST (12 MONTHS) USING THE MONTE CARLO SIMULATION

It is assumed the forecast was conducted at the end of FY13.

- LogNormal distribution parameters for the Crystal Ball forecast model: μ = 1,424; σ = 256; location: 0.
- For predicting lead-time demand, we used actual demand data in a 48 month window from FY10 to FY13 and excluded one outlier value in Sept-13.
- Lead-time demand during twelve months = 17,086 units.
- 95% fill rate = lead-time demand + safety stock = 18,585 units

The Monte Carlo simulations below show forecasts for twelve months (lead time) and six months (to gauge forecast model performance against the actual FY14 demand). Actual demand data for October 2013 to March 2014 was known. Therefore, we used the six-month forecast to gauge performance (forecast error between the model and the real world. The forecasts are depicted in Figures 102 and 103.

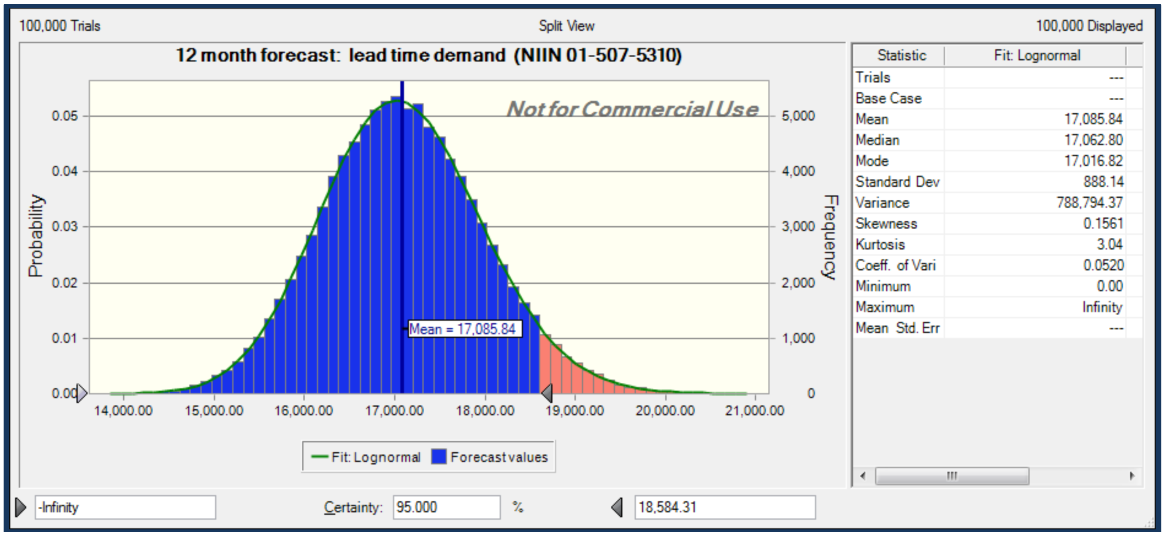

Figure 102. NIIN 01-507-5310 12-Month Forecast Simulation

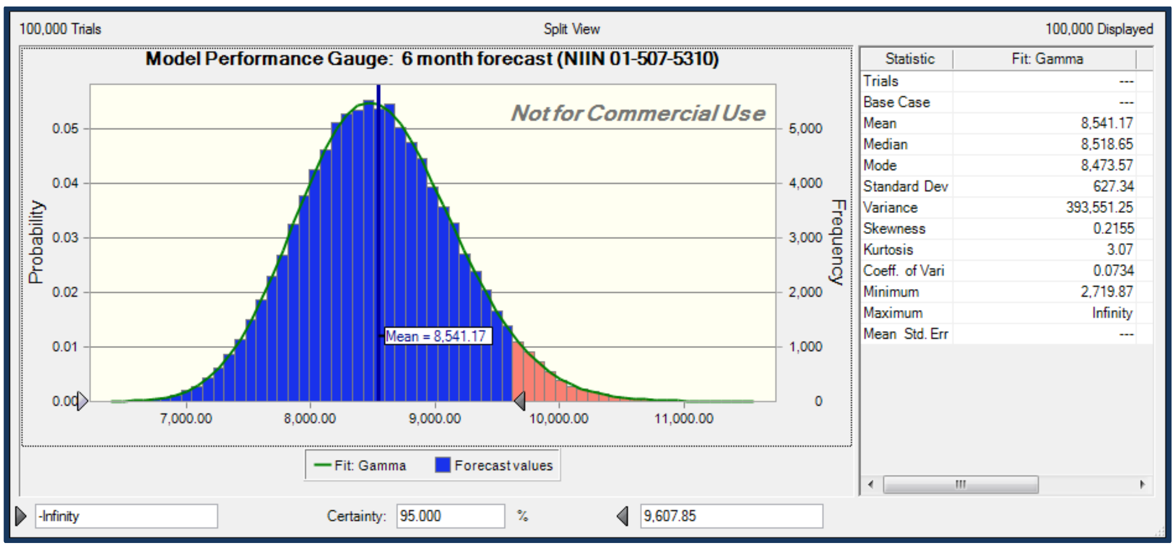

Figure 103. NIIN 01-507-5310 6-Month Forecast Simulations

- **Observations from the First Forecast**

It is assumed the observations from the first forecast were compiled after a 6 month lapse, at the end of March 2014. Figure 104 compares the FY14 actual demand versus the Monte Carlo forecast simulation of October 2013 and shows a low forecast error of 2%. If the product-demand forecast was used to formulate inventory policy, DLA would realize significant inventory cost reduction because the actual inventory is high (see paragraph 4, inventory policy section below).

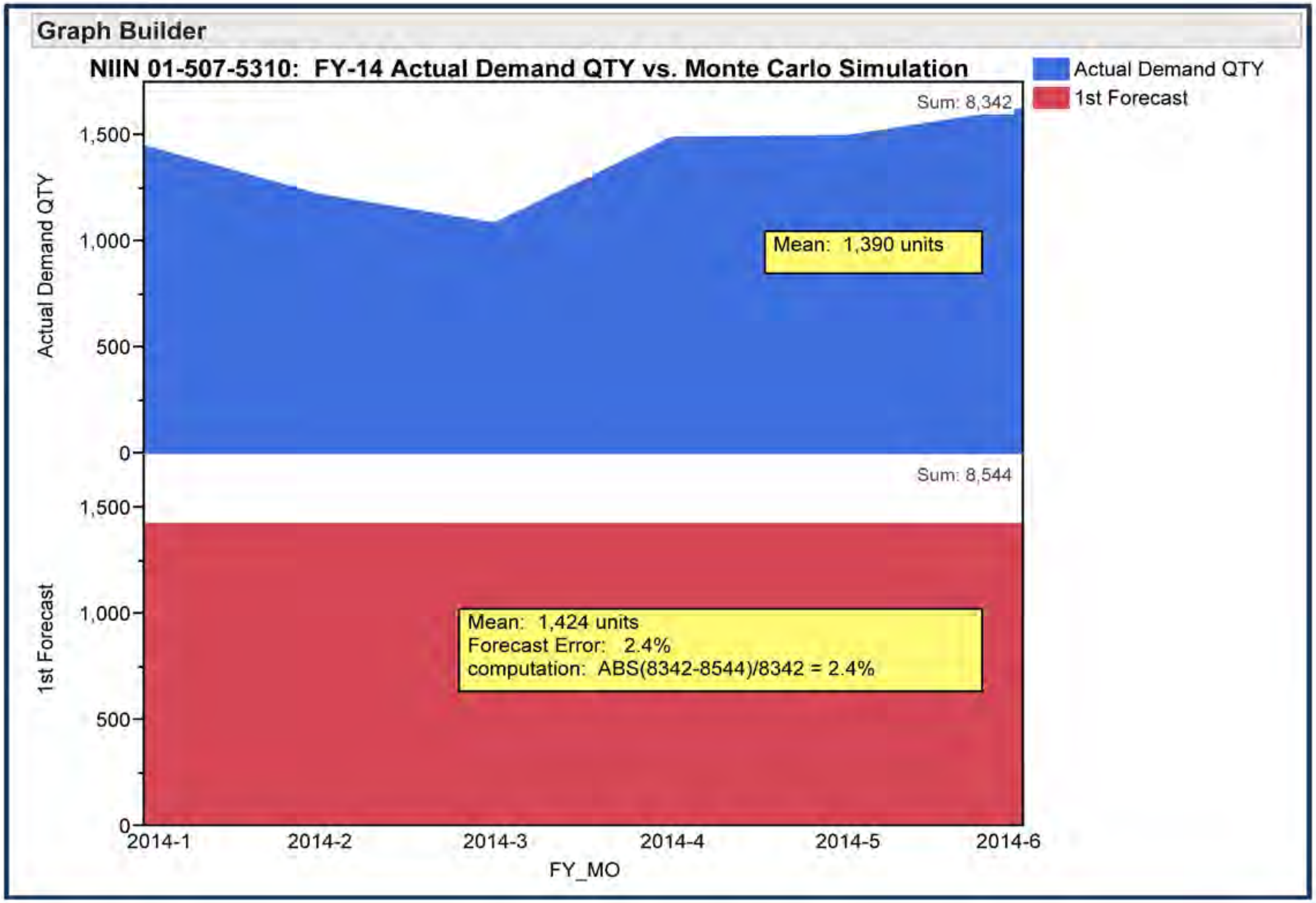

Figure 104. NIIN 01-507-5310 Monte Carlo Forecast Model versus Actual FY14 Demand

Table 25 compares the results of the first forecast against actual product demand during the first six months of FY14. The lead-time demand forecast is also provided (shaded gray). Notice the forecast reorder point is 18,584 units.

Six Month Forecast: Comparison of the forecast model vs. actual demand			
		Average	Average
FY_MO	Actual Product Demand	Forecast: 1st model	Forecast: 2nd model
2014-1	1448	1423.53	
2014-2	1214	1423.53	
2014-3	1081	1423.53	
2014-4	1484	1423.53	
2014-5	1495	1423.53	
2014-6	1620	1423.53	
Total	**8342**	**8541.17**	**0**
		Oct. 2013 six month forecast error:	
Delta forecast #1	199.17	ABS(8342-8541)/8342 = *2%*	Apr. 2014 six month forecast error:

All forecasts:		
FY 2014, six months:	8,541	
FY 2014, twelve months:	17,086	
Lead Time demand, 12 months:	*17,086*	
Reorder Point:	18,584	

The market for this product is non-static, characterized by shifting conditions.

Table 25. NIIN 01-507-5310 Comparison First Forecast versus Actual Demand

- **Forecast update**

For this research, a second forecast would normally be run and we would assume this forecast was conducted on the first week of April 2014 (mid-year forecast update). However, a second forecast simulation was not conducted, due to the high accuracy of the first forecast model.

D. INVENTORY POLICY FORMULATION: AS CONDITIONS CHANGE, SO MUST INVENTORY POLICY

The results of the Monte Carlo simulation provide guidance for inventory policy change. Take note of both the mean lead time demand (17,086) and 95% service level (18,584) values.

- Lead-time demand = mean

- Reorder point = 95% service level

Whereas DLA inventory policy for FY14 set the reorder point of 22,127 units, the October 2013 forecast called for a reorder point of 18,584 units. That is a difference of 3,543 units. At a FY14 price of about $756 per unit, the inventory cost reduction would be $2.6 million (with selling price used in lieu of cost), as presented in Table 25.

Evolving Inventory Policy: Narrowing the gap beween the model and the real world			
	Actual DLA QTY	1st forecast	**2nd forecast**
Effective date:	**FY 14**	Oct-13	**Apr-14**
Forecast		17,086	**0**
Safety Stock:	**1,915**	1,498	**0**
Reorder Point:	**22,127**	18,584	**0**
The market for this product is non-static, characterized by shifting conditions and uncertainty.			
The Apr-14 forecast used 6 months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.			
FY-14 unit price	Delta	**cost savings**	**cost increase**
$756	3,543	**$2,678,508**	

Table 26. NIIN 01-507-5310 Forecast Model versus Real World Demand.

Since this NIIN is a class-A item (per Chapter III), it should be managed with a continuous inventory policy, due to this product's impact on (potential) overall annual revenue.

As the JMP software training (online) states, "All [forecast] models are wrong, but some are useful… The illustration below, Figure 104, states that the organization's performance is a function of their learning curve." See how this statement applies to inventory policy formulation in the next section as it discusses the cost reduction benefit of reducing lead time.

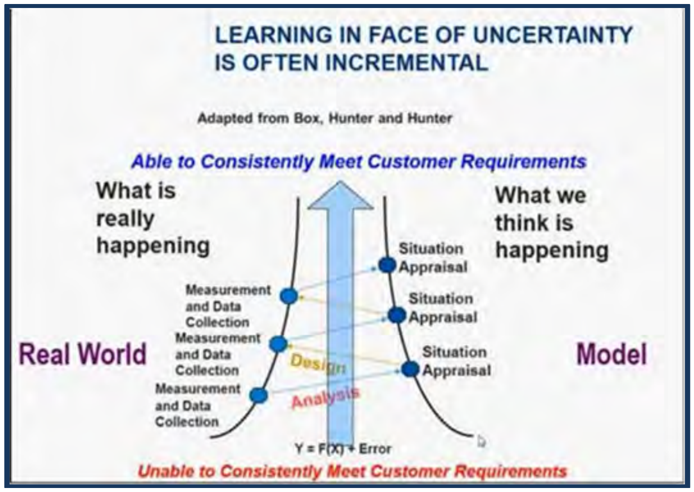

Figure 105. Learning curve, adopted from Exploring Best Practices in Design of Experiments SAS Institute (Webinar 2014)

E. CONDITIONAL VALUE AT RISK ANALYSIS

The graph in Figure 106 shows the lead-time demand forecast. The 95% service level is shaded blue and the value of this area under the demand curve is 18,584 units. The remaining 5% is the conditional value at risk (right tail of the distribution curve). Figure 107 presents the range of values of the conditional value at risk (if stock runs out, what is the expected amount?).

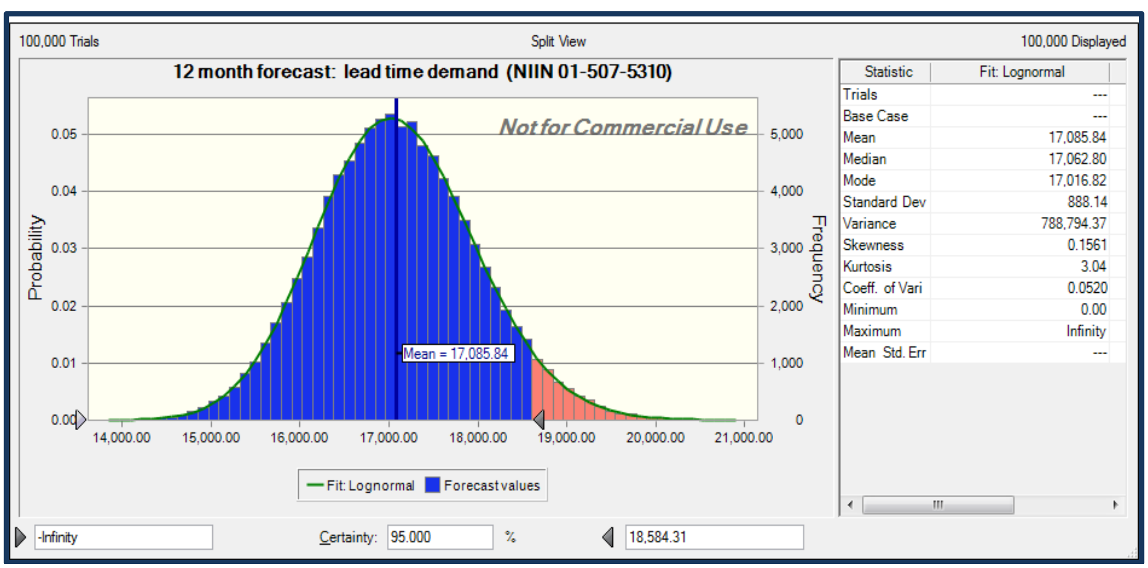

Figure 106. NIIN 01-507-5310 12-Month Lead Time Demand Forecast

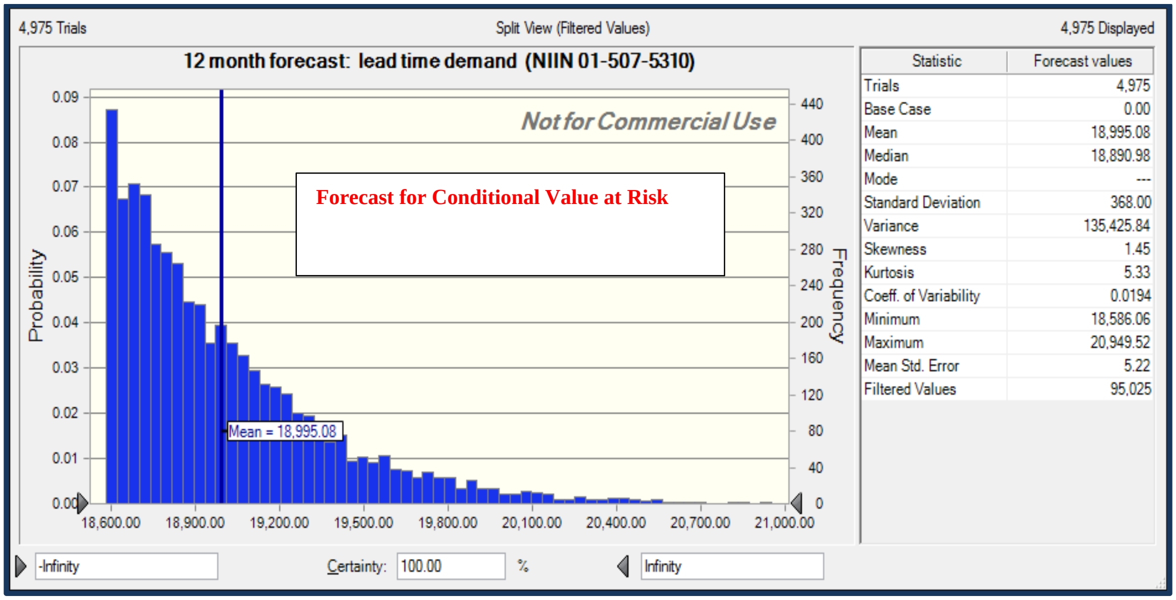

Figure 107. NIIN 01-507-5310 Conditional Value at Risk

As shown in Table 27, we draw the following conclusions from the Monte Carlo simulation:

The average lead-time demand forecast (50% probability	**17,086 units** (lead time = 12 months)
A 95% fill rate quantity equals	**18,584 units** of inventory
Conditional risk: If demand exceeds stock on hand during the replenishment cycle, the expected shortage is	**411 units** (see forecast right tail distribution: 18,995 – 18,584 = 411)
How bad can things get if there is a stock out? The maximum shortage forecasted is	**3,364 units** (20,950 – 18,584 = 2,366)

Table 27. NIIN 01-507-5310 Lead Time Demand Forecast and Stock out Risk Analysis Summary Table

a. Improving the Organization's Learning Curve

The organization should produce demand forecasts and risk analysis for this NIIN on a quarterly basis at least and adjust the inventory policy (reorder point and safety stock

levels) as required. This implies integrated planning with the contracting officer and item manager for negotiating the right procurement contract with the supplier(s).

b. Learning-Curve Potential

Tables 28 and Figure 108 illustrate that lead time for this NIIN is 345 days (or about twelve months). Reducing the replenishment lead time (admin + procurement) would reduce the exposure period of demand uncertainty and would likely lead to lower safety stock and reorder points, and thus, lower inventory costs.

Lead Time (FY-14)	NIIN 015075310
procurement lead time days:	15
admin lead time days:	330
total days:	345
months	**11.5**

Table 28. NIIN 01-507-5310 Admin and Procurement Lead Time

Tabulate

							qty_req	Revenue	alt		plt
FY	FY_QTR	FY_MO series	Calendar Month	niin	itm_name	std_u_price	Sum	Sum	15	30	330
2010	2010-1	1	10	015075310	THERMOCOUPLE,CONTAC	682.69	1,774	$1,211,092	0	24	24
		2	11	015075310	THERMOCOUPLE,CONTAC	682.69	1,488	$1,015,843	0	22	22
		3	12	015075310	THERMOCOUPLE,CONTAC	682.69	2,114	$1,443,207	0	22	22
	2010-2	4	1	015075310	THERMOCOUPLE,CONTAC	682.69	2,020	$1,379,034	0	23	23
		5	2	015075310	THERMOCOUPLE,CONTAC	682.69	2,002	$1,366,745	0	18	18
		6	3	015075310	THERMOCOUPLE,CONTAC	682.69	2,417	$1,650,062	0	21	21
	2010-3	7	4	015075310	THERMOCOUPLE,CONTAC	682.69	2,543	$1,736,081	0	20	20
		8	5	015075310	THERMOCOUPLE,CONTAC	682.69	1,998	$1,364,015	0	25	25
		9	6	015075310	THERMOCOUPLE,CONTAC	682.69	3,325	$2,269,944	0	24	24
	2010-4	10	7	015075310	THERMOCOUPLE,CONTAC	763.55	2,544	$1,942,471	0	24	24
		11	8	015075310	THERMOCOUPLE,CONTAC	763.55	2,746	$2,096,708	0	28	28
		12	9	015075310	THERMOCOUPLE,CONTAC	763.55	3,546	$2,707,548	0	22	22
2011	2011-1	1	10	015075310	THERMOCOUPLE,CONTAC	763.55	1,787	$1,364,464	0	19	19
		2	11	015075310	THERMOCOUPLE,CONTAC	763.55	852	$650,545	0	17	17
		3	12	015075310	THERMOCOUPLE,CONTAC	763.55	2,187	$1,669,884	0	20	20
	2011-2	4	1	015075310	THERMOCOUPLE,CONTAC	763.55	1,590	$1,214,045	0	20	20
		5	2	015075310	THERMOCOUPLE,CONTAC	763.55	1,584	$1,209,463	0	19	19
		6	3	015075310	THERMOCOUPLE,CONTAC	763.55	2,063	$1,575,204	0	21	21
	2011-3	7	4	015075310	THERMOCOUPLE,CONTAC	763.55	1,797	$1,372,099	0	22	22
		8	5	015075310	THERMOCOUPLE,CONTAC	763.55	2,198	$1,678,283	0	27	27
		9	6	015075310	THERMOCOUPLE,CONTAC	763.55	2,072	$1,582,076	0	22	22
	2011-4	10	7	015075310	THERMOCOUPLE,CONTAC	754.28	1,948	$1,469,337	0	22	22
		11	8	015075310	THERMOCOUPLE,CONTAC	754.28	2,251	$1,697,884	0	22	22
		12	9	015075310	THERMOCOUPLE,CONTAC	754.28	3,305	$2,492,895	0	24	24
2012	2012-1	1	10	015075310	THERMOCOUPLE,CONTAC	754.28	1,771	$1,335,830	0	23	23
		2	11	015075310	THERMOCOUPLE,CONTAC	754.28	1,300	$980,564	0	15	15
		3	12	015075310	THERMOCOUPLE,CONTAC	754.28	1,725	$1,301,133	0	27	27
	2012-2	4	1	015075310	THERMOCOUPLE,CONTAC	727.88	2,292	$1,668,301	22	0	22
		5	2	015075310	THERMOCOUPLE,CONTAC	727.88	1,323	$962,985	19	0	19
		6	3	015075310	THERMOCOUPLE,CONTAC	727.88	1,311	$954,251	16	0	16
	2012-3	7	4	015075310	THERMOCOUPLE,CONTAC	727.88	1,360	$989,917	16	0	16
		8	5	015075310	THERMOCOUPLE,CONTAC	727.88	1,622	$1,180,621	19	0	19
		9	6	015075310	THERMOCOUPLE,CONTAC	727.88	3,139	$2,284,815	14	0	14
	2012-4	10	7	015075310	THERMOCOUPLE,CONTAC	710.41	2,137	$1,518,146	20	0	20
		11	8	015075310	THERMOCOUPLE,CONTAC	710.41	1,229	$873,094	20	0	20
		12	9	015075310	THERMOCOUPLE,CONTAC	710.41	3,253	$2,310,964	19	0	19
2013	2013-1	1	10	015075310	THERMOCOUPLE,CONTAC	710.41	1,314	$933,479	23	0	23
		2	11	015075310	THERMOCOUPLE,CONTAC	710.41	803	$570,459	18	0	18
		3	12	015075310	THERMOCOUPLE,CONTAC	710.41	1,339	$951,239	15	0	15
	2013-2	4	1	015075310	THERMOCOUPLE,CONTAC	710.41	6,256	$4,444,325	22	0	22
		5	2	015075310	THERMOCOUPLE,CONTAC	710.41	1,989	$1,413,005	19	0	19
		6	3	015075310	THERMOCOUPLE,CONTAC	710.41	2,576	$1,830,016	22	0	22
	2013-3	7	4	015075310	THERMOCOUPLE,CONTAC	710.41	1,379	$979,655	21	0	21
		8	5	015075310	THERMOCOUPLE,CONTAC	710.41	1,654	$1,175,018	21	0	21
		9	6	015075310	THERMOCOUPLE,CONTAC	710.41	1,908	$1,355,462	19	0	19
	2013-4	10	7	015075310	THERMOCOUPLE,CONTAC	756.11	2,132	$1,612,027	22	0	22
		11	8	015075310	THERMOCOUPLE,CONTAC	756.11	1,701	$1,286,143	22	0	22
		12	9	015075310	THERMOCOUPLE,CONTAC	756.11	1,552	$1,173,483	23	0	23
2014	2014-1	1	10	015075310	THERMOCOUPLE,CONTAC	756.11	1,448	$1,094,847	14	0	14
		2	11	015075310	THERMOCOUPLE,CONTAC	756.11	1,214	$917,918	18	0	18
		3	12	015075310	THERMOCOUPLE,CONTAC	756.11	1,081	$817,355	14	0	14
	2014-2	4	1	015075310	THERMOCOUPLE,CONTAC	756.11	1,484	$1,122,067	18	0	18
		5	2	015075310	THERMOCOUPLE,CONTAC	756.11	1,495	$1,130,384	15	0	15
		6	3	015075310	THERMOCOUPLE,CONTAC	756.11	1,620	$1,224,898	16	0	16

Figure 108. NIIN 01-507-5310 Monthly Demand, Admin Lead Time and Production Lead Time

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APPENDIX D. LEAD-TIME DEMAND FORECASTS FOR NIIN 011707951 AIRCRAFT FAIRING

Information found in this section regarding product-demand forecast for the aircraft fairing includes:

A. Statistical analysis of product demand

B. Observations from the statistical analysis

C. Lead-time-demand forecast: an input for inventory policy

D. Inventory-policy formulation

E. Conditional value at risk analysis

A. STATISTICAL ANALYSIS OF PRODUCT DEMAND

Demand for this product was non-static and highly variable from FY10 to FY13. In Figure 109, the outlier value of 76,390 units dominates demand during this time period. “Dominates” is used here to mean that a month’s demand hit single-handedly pulls the average monthly demand for this product in one direction (up to 1,686 units).

In Figure 110, the outlier value (QTY = 76,390 units) was excluded. Notice the dramatic decrease in mean monthly demand from 1,686 to 97 units (rounded up). This graph also helps to better visualize the monthly demand variability across time from FY10 to FY13. Something to keep in mind is that those 76,390 units in FY13 (shown in the graph above) should nullify some product demand that would have been present in FY14. Therefore, although, the general trend is small increases in demand across succeeding fiscal years starting in FY10, our hypothesis is that the outlier value in FY13 might cause a shift downward in the overall demand pattern in FY14 (and beyond).

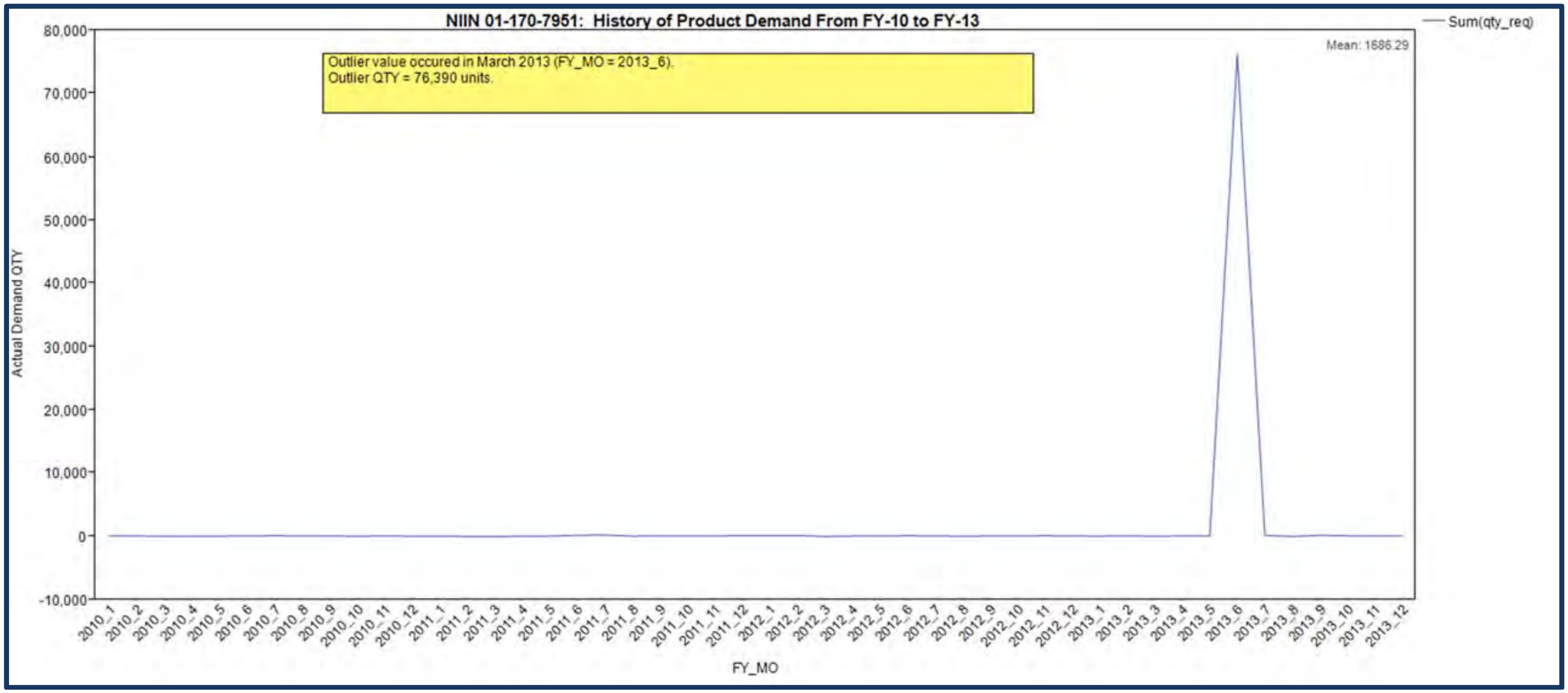


Figure 109. NIIN 01-170-7951 Monthly Demand Data for FY10 - FY13

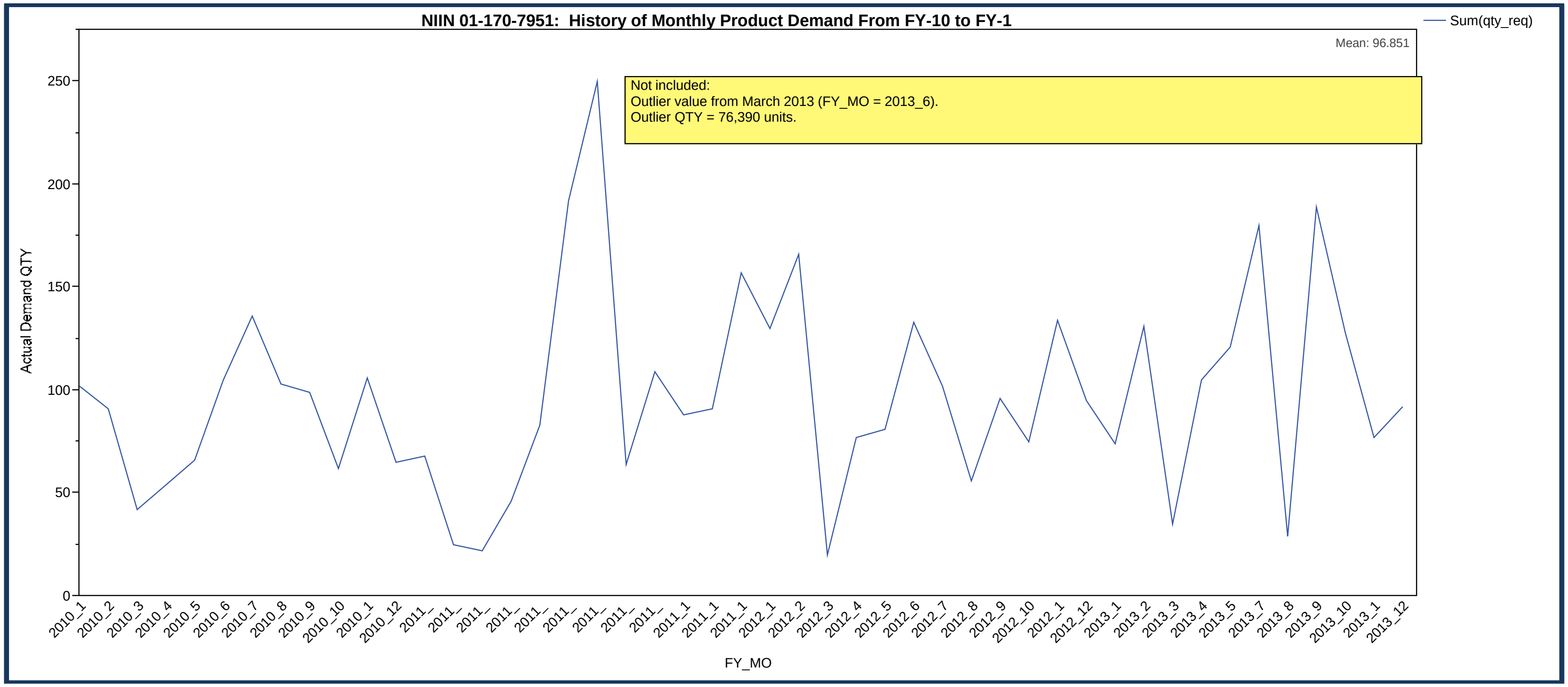


Figure 110. NIIN 01-170-7951 Monthly Demand Data for FY10 - FY13 without Outlier

The graphs in Figure 111 help visualize demand variability. The outlier value discussed above is excluded.

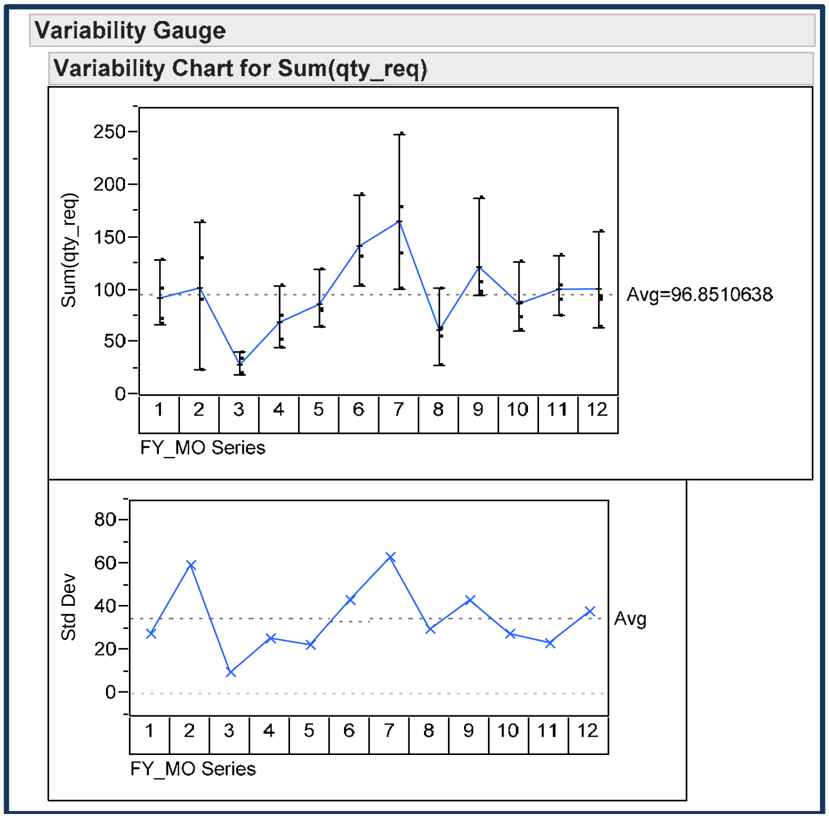


Figure 111. NIIN 01-170-7951 Monthly Demand Variability

Figures 112 and 113 clearly show a trend of increased (mean) demand across fiscal years. Again, our hypothesis is that FY14 will experience a downward shift in demand because of the outlier value in March 2013 (76,390 units).

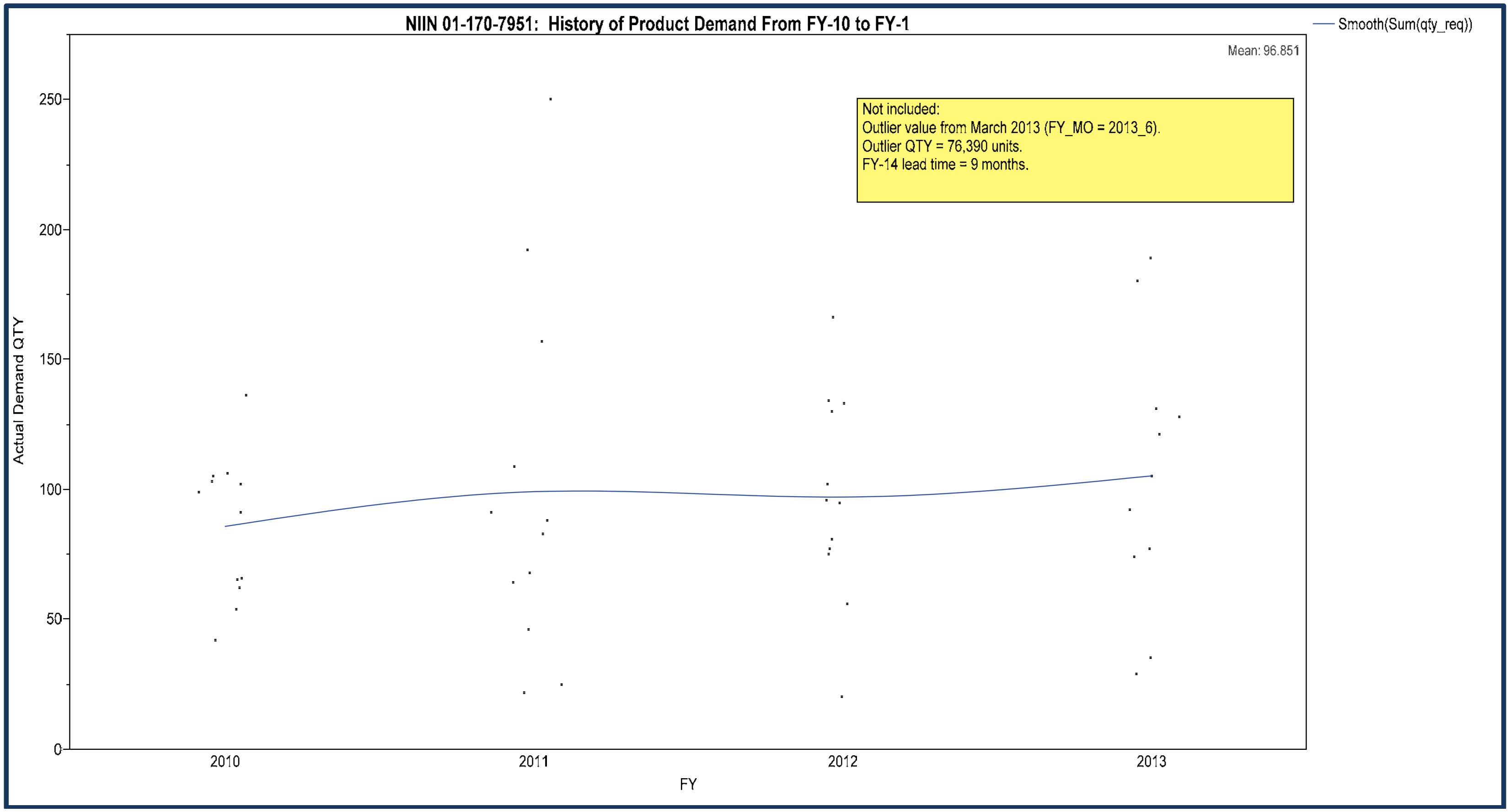


Figure 112. NIIN 01-170-7951 Demand History FY10 – FY13 (A)

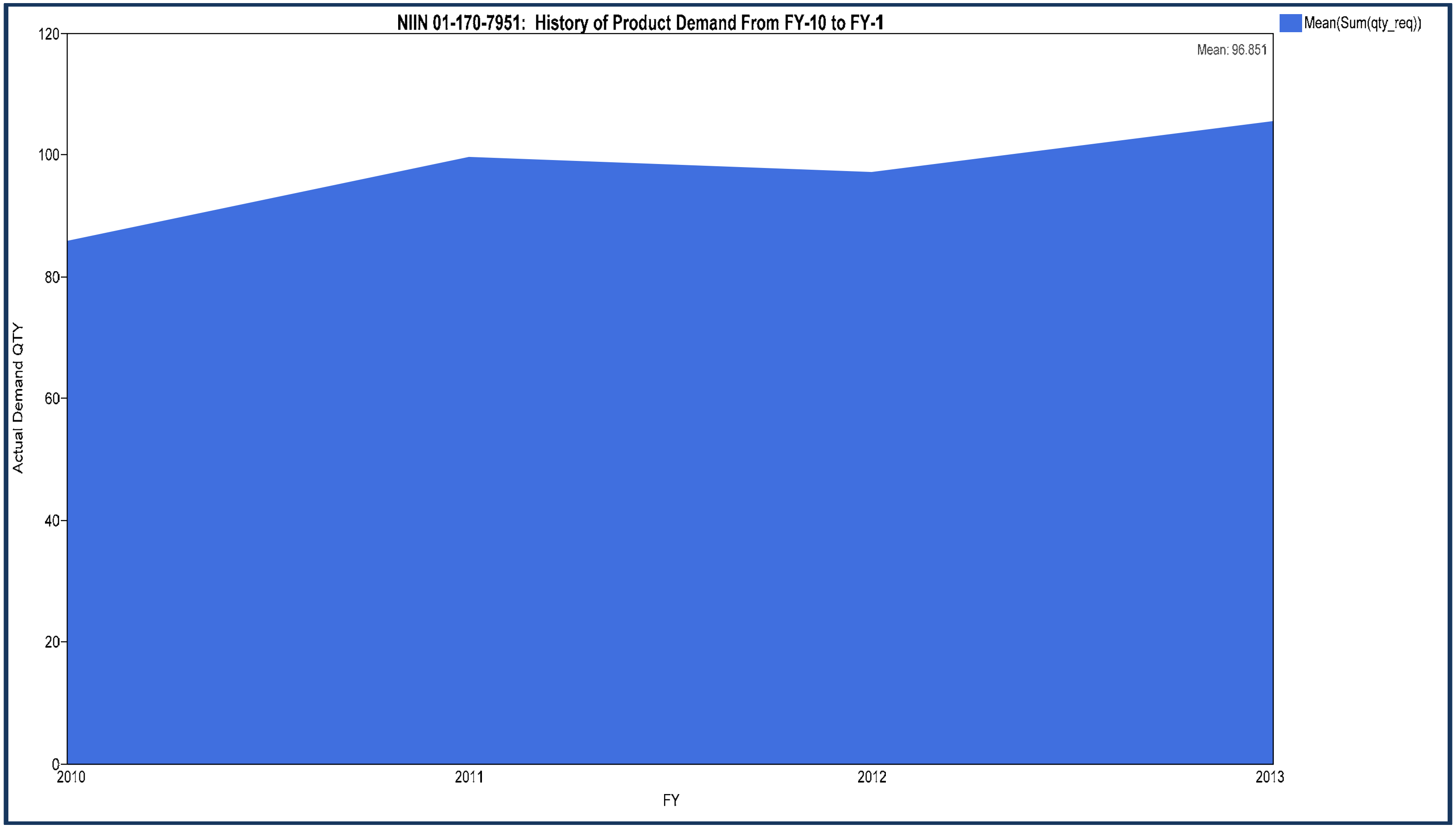
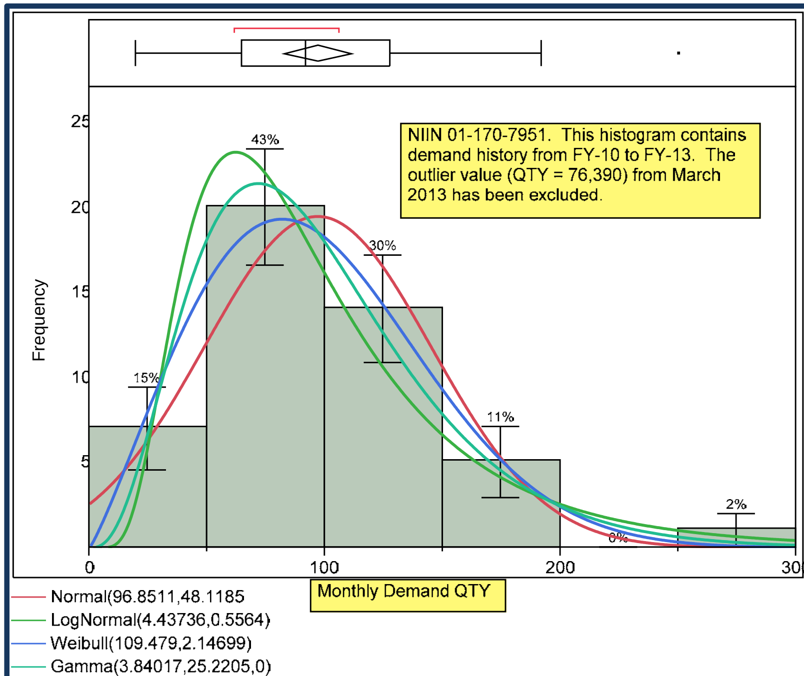


Figure 113. NIIN 01-170-7951 Demand History FY10 – FY13 (B)

- **Probability Distribution Analysis**

Various probability distributions have been fit to the demand data encompassing four fiscal years as shown in Figure 114. The outlier value (QTY = 76,390) is not included; the highest monthly demand value is QTY = 250 units and the mean value is 97 units (rounded up). We are searching for a useful range of values of product demand; therefore, we must avoid using overinflated values for our forecast model.



Quantiles

100.0%	maximum	250
99.5%		250
97.5%		238.4
90.0%		168.8
75.0%	quartile	128
50.0%	median	92
25.0%	quartile	65
10.0%		33.8
2.5%		20.4
0.5%		20
0.0%	minimum	20

Summary Statistics

Mean	96.851064
Std Dev	48.118504
Std Err Mean	7.0188051
Upper 95% Mean	110.97919
Lower 95% Mean	82.722942
N	47
Sum	4,552
Variance	2315.3904
Skewness	0.8551974
Kurtosis	1.2045658
Median	92
Mode	77
Range	230
Interquartile Range	63

Note: The mode shown is the smallest of 4 modes with a count of 2.

Figure 114. NIIN 01-170-7951 FY10 to FY13 Demand Data Histogram

JMP software used the product-demand range from the histogram above to generate the prediction-interval section below in the green box. Notice: The lower–upper range in both the mean (μ) value and standard deviation are relatively large. Recall that an increasing trend seems to dominate the pattern of product demand from FY10 to FY13. However, as discussed above, the outlier demand value in FY13 could have zapped out some demand that would be observed in FY14. Thus, as shown in Figure 115 the "lower PI" mean confidence level for monthly demand could be the most valid parameters for our forecast model ($\mu = 54.86$; $\sigma = 19.39$).

Associated with the mean and standard deviation numbers discussed above, the "fitted Weibull" section in the orange box in Figure 116 shows the P-value is .25. Therefore, there is not enough evidence to reject the hypothesis, "demand data follows a Weibull distribution." The parameters found in this section appear reasonable; therefore, at this point we favor the lower 95% confidence level **"Fitted Weibull" parameters (scale = 94.6; shape = 2)** in conjunction with the Weibull distribution (see orange box below). The Weibull-distribution forecast model requires a lower bound value (location); therefore, we will use zero (0) as the low value for monthly product demand.

Prediction Interval

Parameter	Future N	Lower PI	Upper PI	1-Alpha
Individual	6	-37.224	230.9262	0.950
Mean	6	54.86098	138.8411	0.950
Std Dev	6	19.39603	81.33535	0.950

Figure 115. NIIN 01-170-7951 Prediction Interval

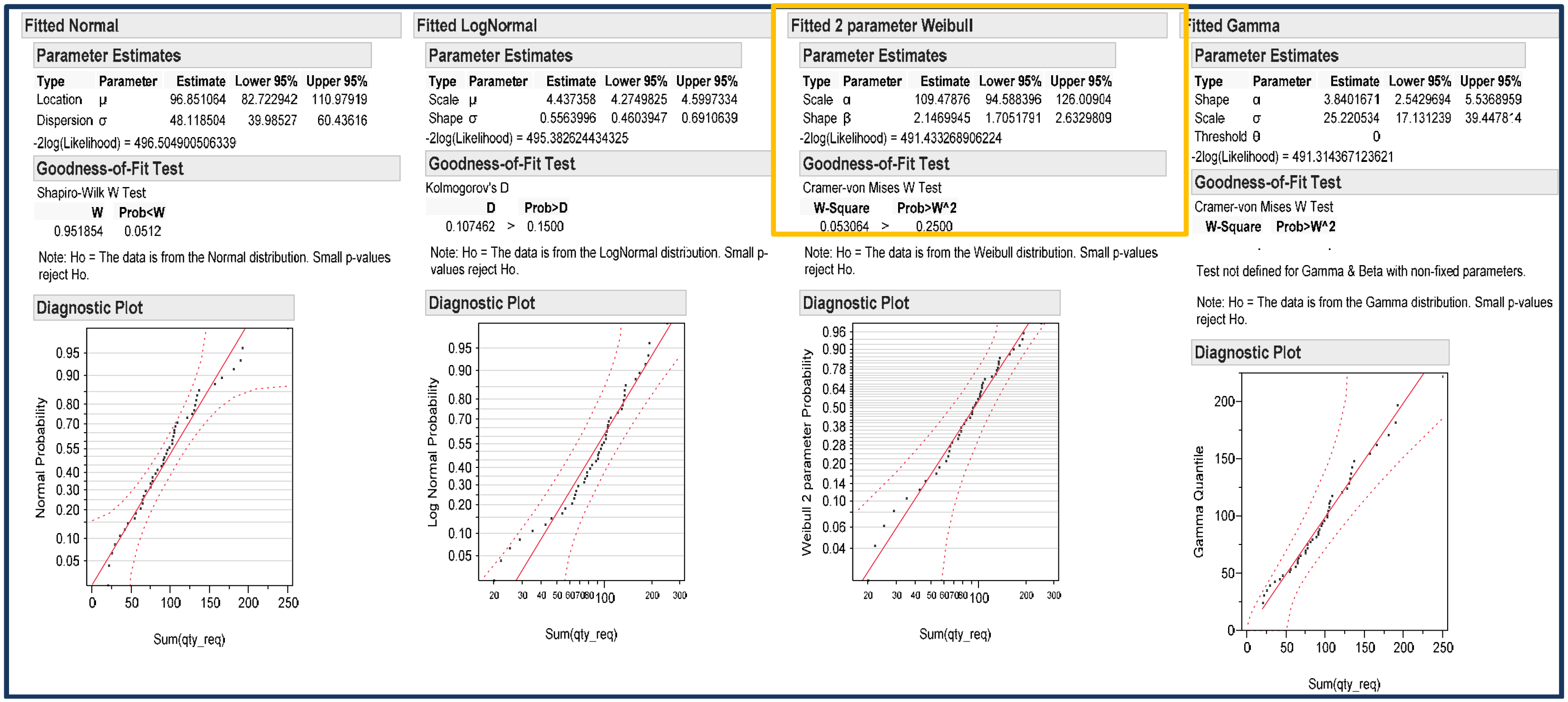


Figure 116. NIIN 01-170-7951 Goodness-Of-Fit Tests

- **Time-Series Analysis of Demand**

Demand during each fiscal year is highly variable; however, the mean value and standard deviation are the strongest indicators of what demand quantity could be during the lead-time demand (demand between replenishment cycles).

The JMP time series forecasts below provide a sensitivity analysis for the demand forecast models that we will build using Crystal Ball.

Compare the section in Figure 115 highlighted in green above, “prediction interval” and the time-series graph below in the green square in Figure 117. The mean values and the standard deviation are significantly different. The prediction interval section shows a lower confidence mean value of 55 units (rounded up), whereas the time-series section below shows a mean value of 96 units.

Two contradicting (and reasonable) predictive sets of information are provided by JMP: on one hand, a gradual increase seems to dominate the pattern of product demand, and on the other, an extreme outlier value that could zap out some of the FY14 product demand. We will conduct a Monte Carlo simulation (forecast model) using the lower spectrum of predictive values in conjunction with the Weibull distribution (with parameters: scale = 94.6; shape = 1.7; location: 0). By lowering the shape from 2 to 1.7, we generate a distribution with lower variability.

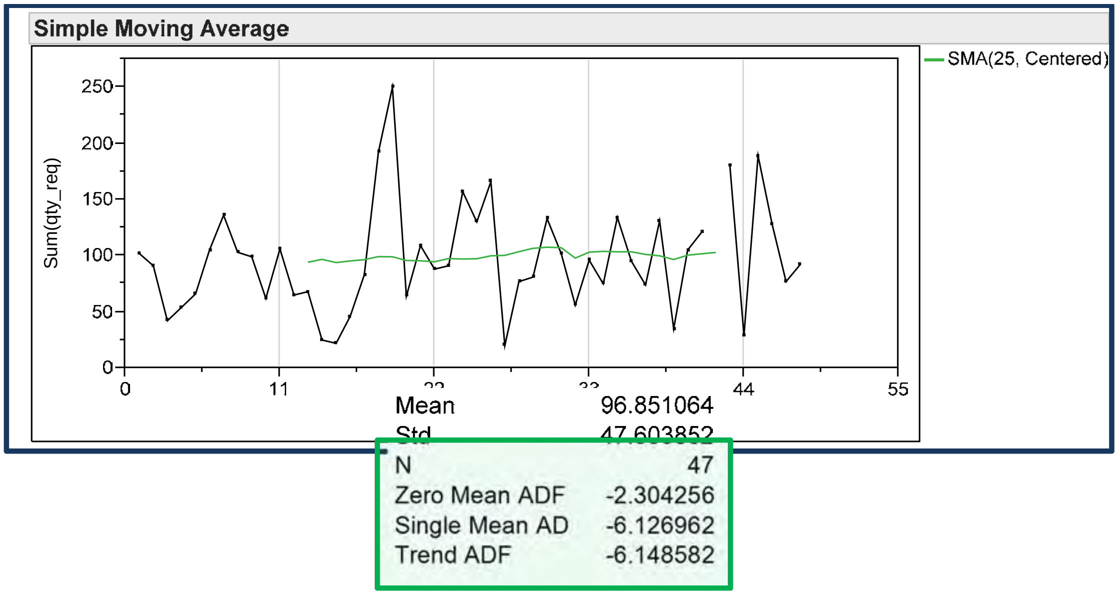


Figure 117. NIIN 01-170-7951 Time Series Prediction Intervals

The JMP time-series analysis produced monthly demand forecasts of between 96 and 125 units; whereas the JMP prediction-interval section generated a lower confidence level of 54 units. If it turns out that there is a decrease in demand in FY14, then the time-series forecasts might be overinflated. This is illustrated in Figures 118– 123.

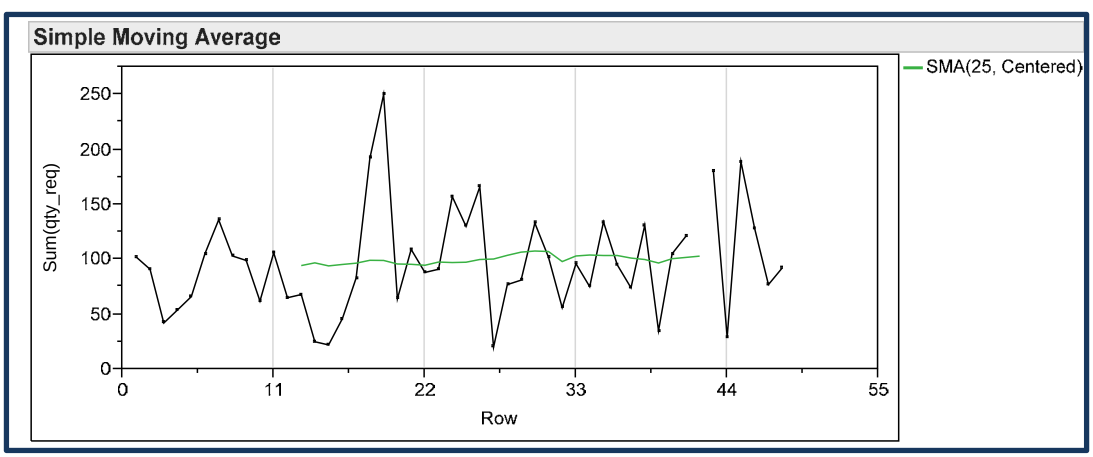


Figure 118. NIIN 01-170-7951 Simple Moving Average Forecast= 0

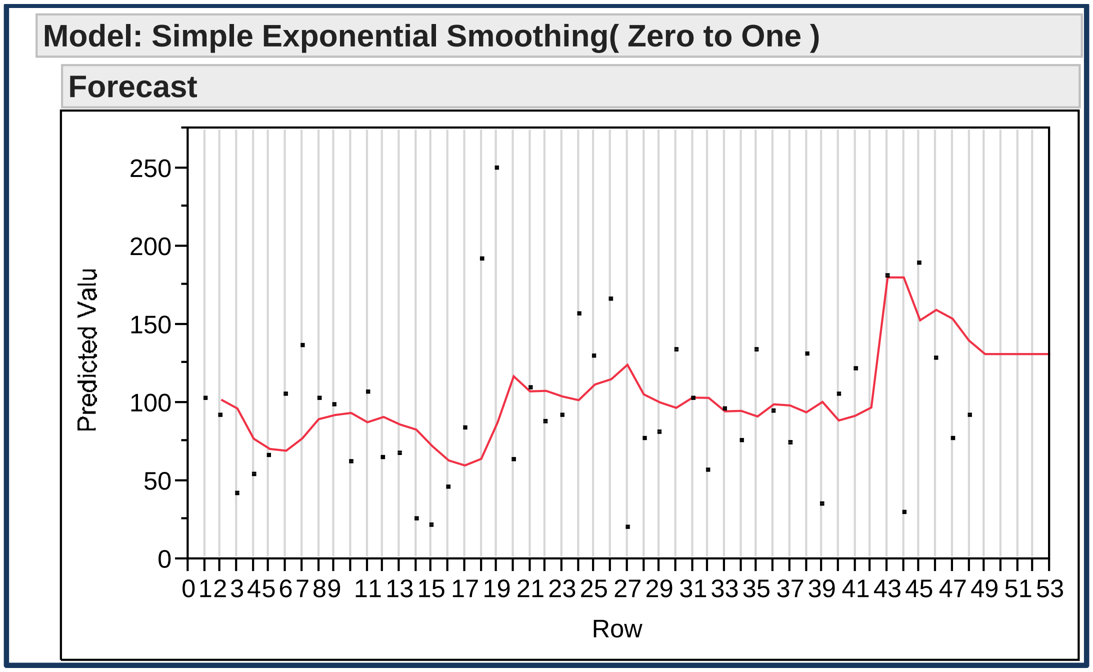


Figure 119. NIIN 01-170-7951 Simple Exponential Smoothing Forecast, Mean Monthly Demand ~125 units

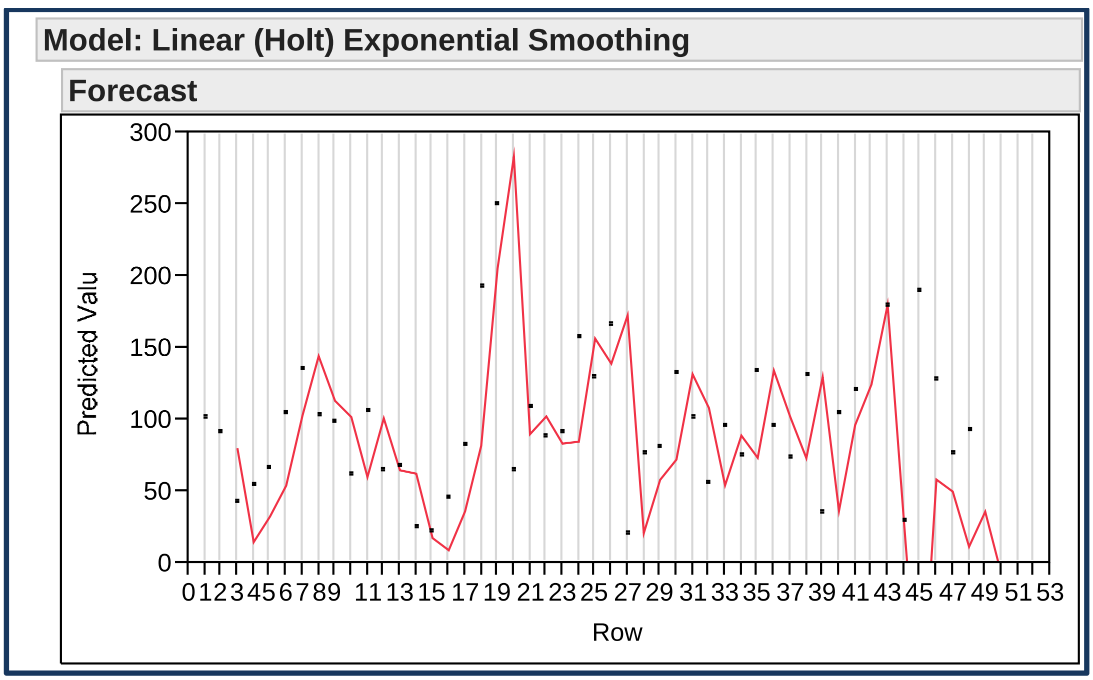


Figure 120. NIIN 01-170-7951 Holt Exponential Smoothing Forecast

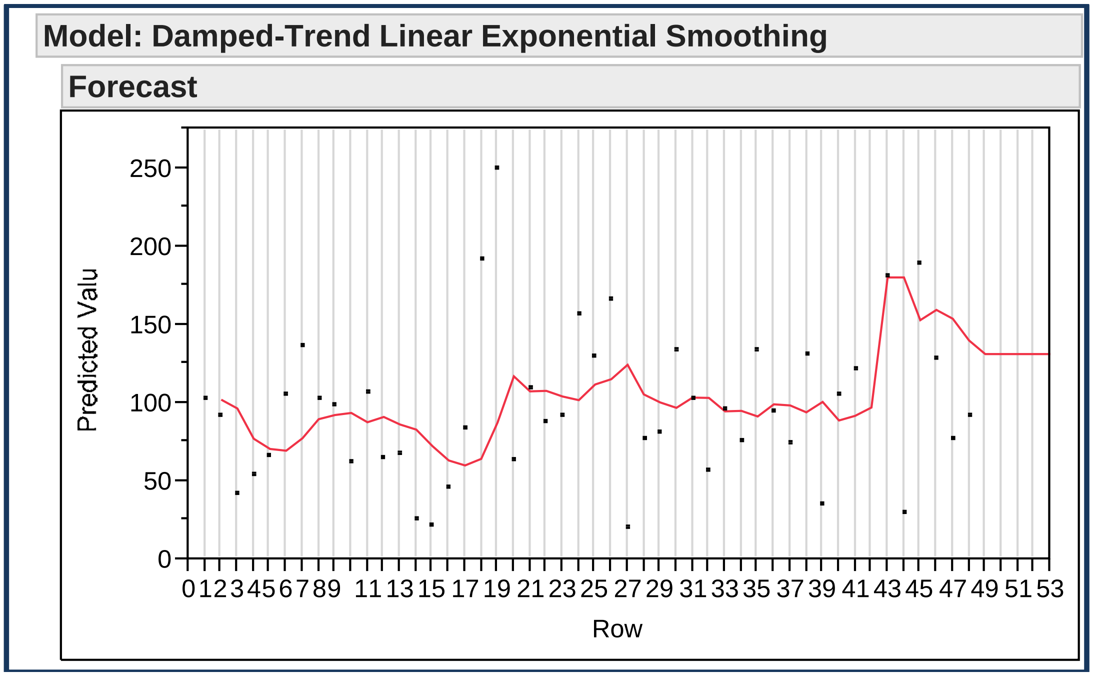


Figure 121. NIIN 01-170-7951 Damped-Trend Linear Exponential Smoothing Forecast

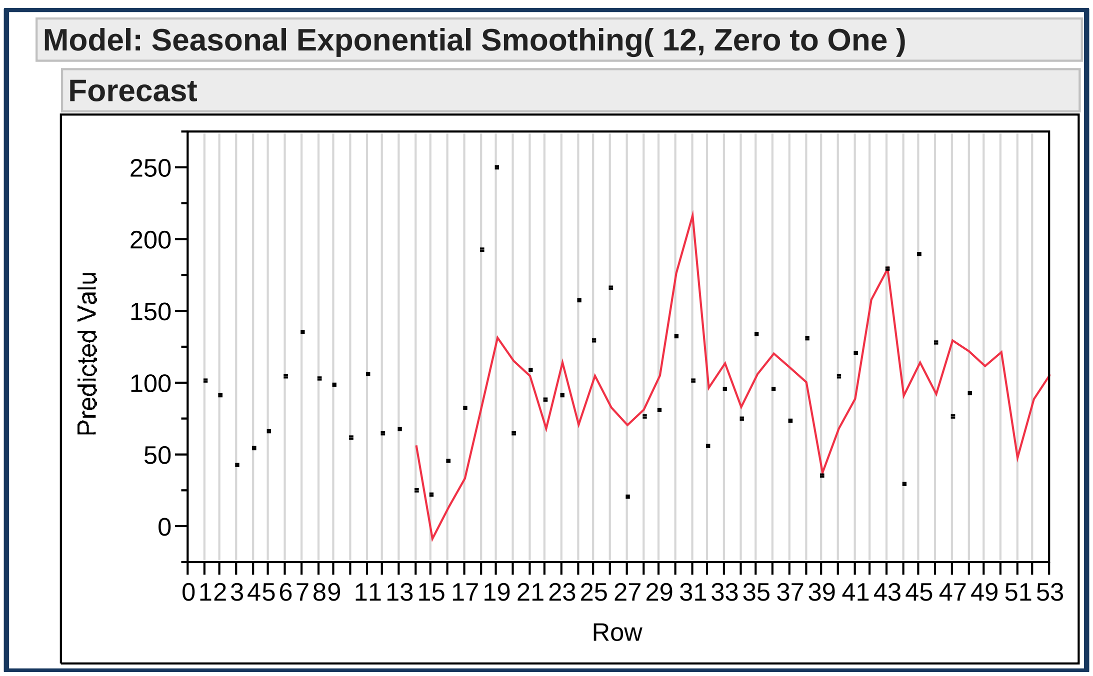


Figure 122. NIIN 01-170-7951 Seasonal Exponential Smoothing Forecast

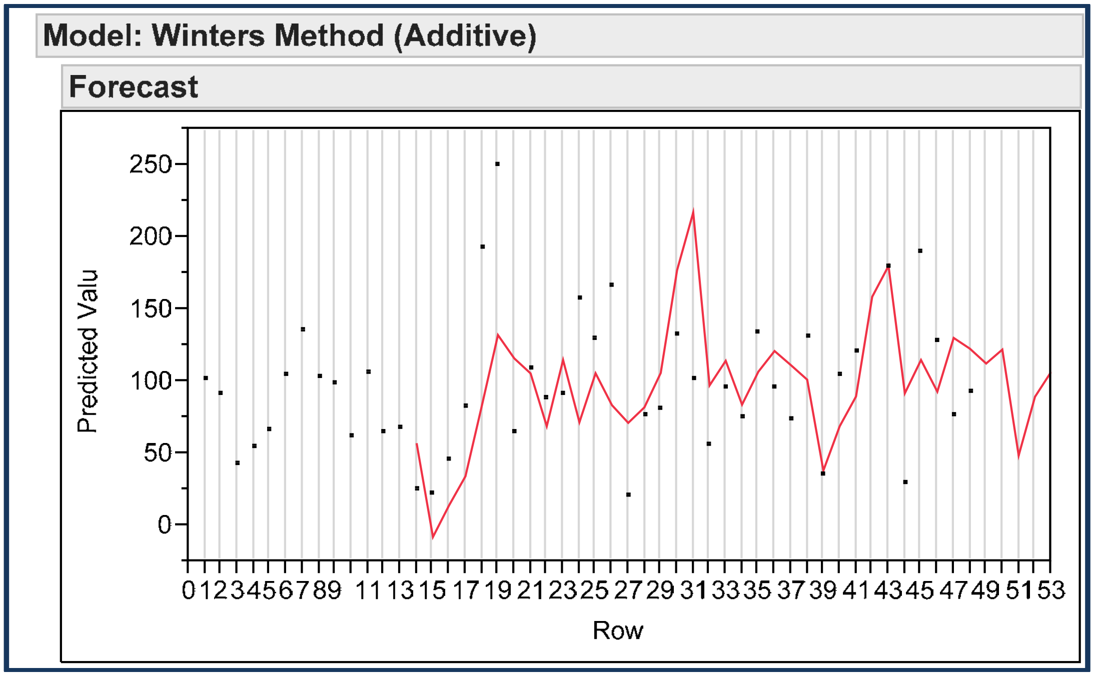


Figure 123. NIIN 01-170-7951 Winters Method Seasonal Exponential Smoothing Forecast

B. OBSERVATIONS FROM THE STATISTICAL ANALYSIS

Under the JMP statistical analysis, the demand for this NIIN appeared non-static and highly variable. Although no adequate probability distribution fit was found, the Weibull distribution had best goodness of fit (highest p-value for a distribution fit).

C. LEAD-TIME DEMAND FORECAST (NINE MONTHS) USING THE MONTE CARLO SIMULATION

- **First forecast**

It is assumed that this forecast was conducted at the end of FY13. For forecast model input, we used actual demand data in a 48-month window from FY10–FY13 and excluded one outlier value in March 2013.

- Weibull distribution parameters for the Crystal Ball forecast model: scale = 94.6; shape = 1.7; location: 0.
- Lead-time demand during six months = 10,865 units.
- 95% fill rate = lead-time demand + safety stock = 14,130 units

The Monte Carlo simulations show various forecasts from six months (lead time and to gauge forecast model performance against actual FY14 demand) to twelve months (fiscal year 2014). Actual demand data for October 2013 to March 2014 was known. Therefore, we used the six-month forecast to gauge performance (forecast error between the model and the real world). The forecasts are depicted in Figures 124 and 125.

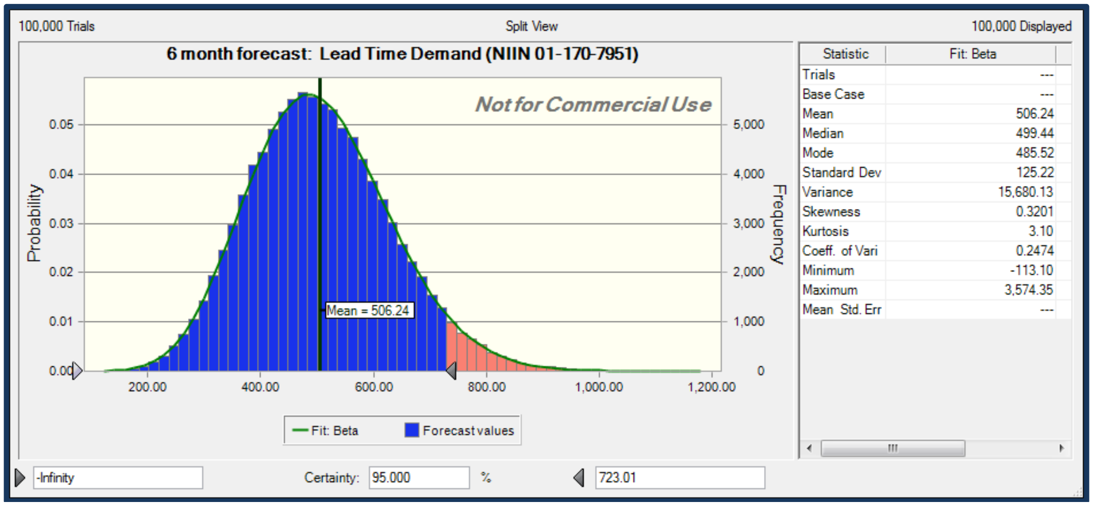


Figure 124. NIIN 01-170-7951 6-Month Forecast Simulation (1st)

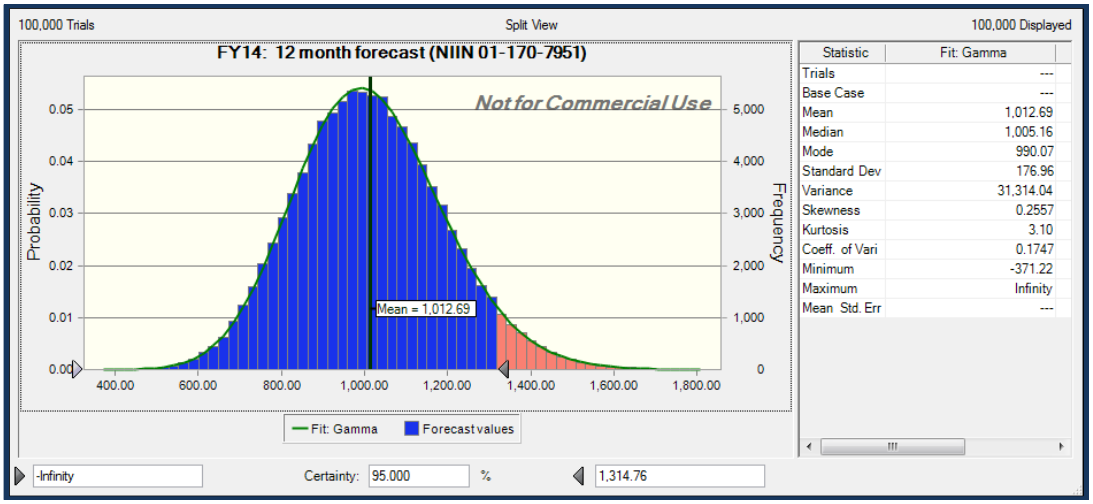


Figure 125. NIIN 01-170-7951 12-Month Demand Forecast Simulation (1st)

- **Observations from the First Forecast**

It is assumed this observation was compiled after a six month lapse in March 2014. Figure 125 shows the forecast error = 29%. If the forecast in Figure 124 was used to formulate inventory policy, DLA would not realize an inventory cost reduction, because the actual inventory is low. However, inventory cost reductions could be realized if the forecast update guidance was executed (see “Apr. 2014 forecast” and inventory-policy section below).

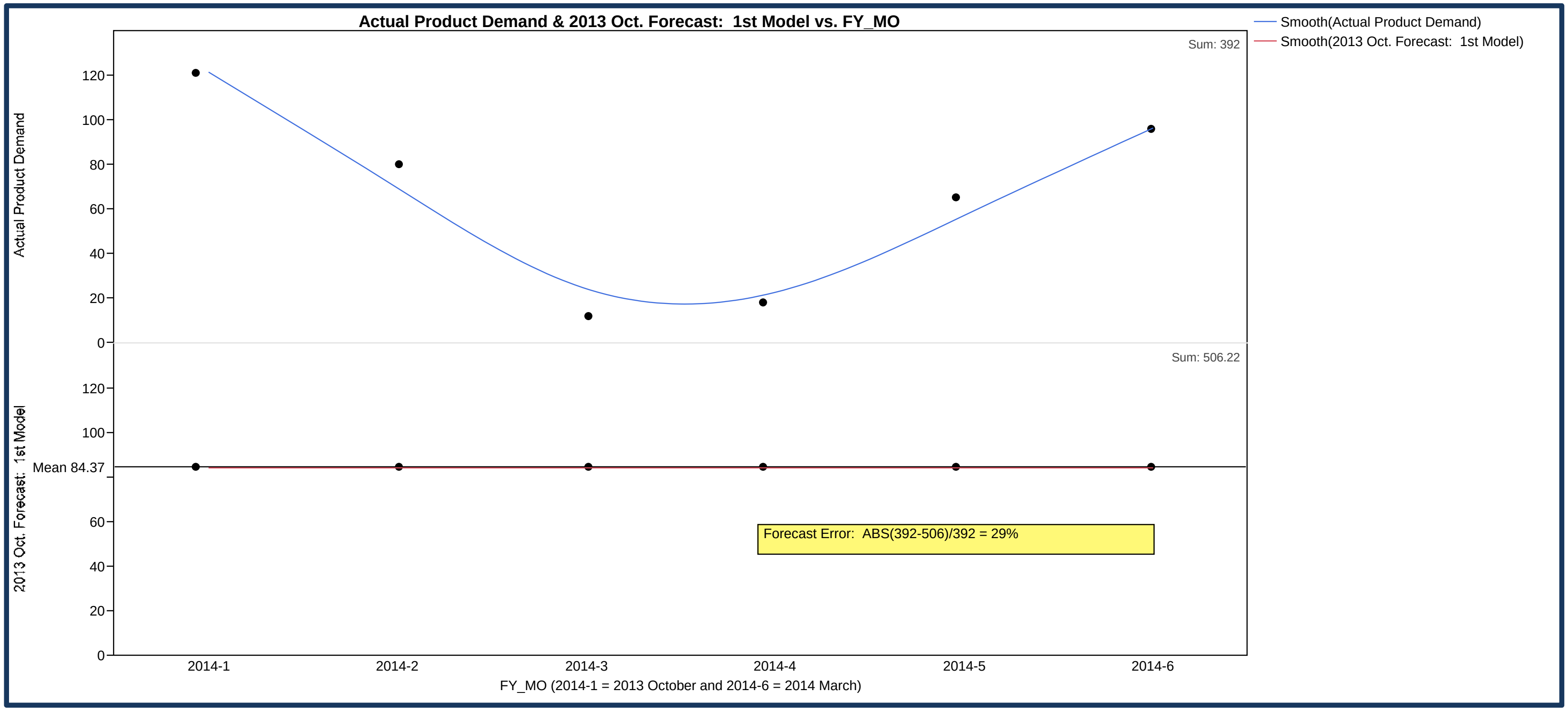


Figure 126. NIIN 01-170-7951 Monte Carlo Forecast Model versus Actual FY 14 Demand (29 % Error)

Table 29 compares the results of the simulation against the actual product demand. The forecasted lead-time demand forecast is also provided (shaded gray).

The market for this product was not static, and there was a decreasing shift in the product demand during the first half of FY14. Hence, the Weibull probability distribution with parameters (scale = 94.6; shape = 1.7 and location = 0) used for the forecast model did not accurately predict demand for the first six months of FY14.

Six Month Forecast: Comparison of the forecast model vs. actual demand

FY_MO	Actual Product Demand	Average Forecast: 1st model	Average Forecast: 2nd model
2014-1	121	84.37	
2014-2	80	84.37	
2014-3	12	84.37	
2014-4	18	84.37	
2014-5	65	84.37	
2014-6	96	84.37	
Total	**392**	**506.24**	**0**
		Oct. 2013 six month forecast error:	
Delta forecast #1	114.24	ABS(392-506)/392 = **29%**	Apr. 2014 six month forecast error:

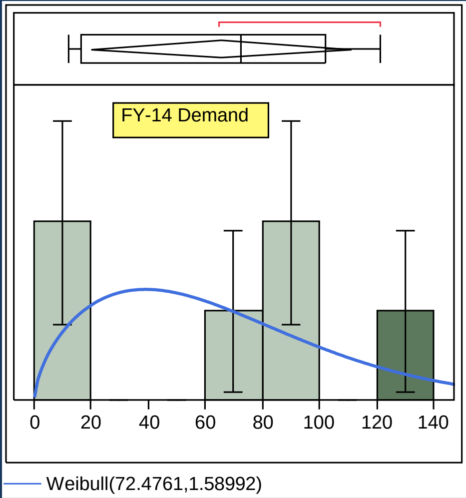
All forecasts:		
FY 2014, six months:	506	
FY 2014, twelve months:	1,013	
Lead Time demand, 6 months:	*506*	
Reorder Point:	723	

The market for this product is non-static, characterized by shifting conditions.

Table 29. NIIN 01-170-7951 Comparison First Forecast versus Actual Demand

- **Second Forecast**

It is assumed this forecast was conducted in the first week of April 2014 (mid-year forecast update). Note in the green box in Figure 127. The mean monthly demand was 65 units (rounded down). However, demand was highly variable, with a standard deviation of 43 units (rounded down).



Quantiles: NIIN 011707951

100.0%	maximum	121
99.5%		121
97.5%		121
90.0%		121
75.0%	quartile	102.25
50.0%	median	72.5
25.0%	quartile	16.5
10.0%		12
2.5%		12
0.5%		12
0.0%	minimum	12

Summary Statistics

Mean	65.333333
Std Dev	43.218823
Std Err Mean	17.644011
Upper 95% Mean	110.68871
Lower 95% Mean	19.97796
N	6
Variance	1867.8667
Skewness	-0.197917
Kurtosis	-1.506273
Median	72.5
Mode	.
Range	109
Interquartile Range	85.75

Figure 127. NIIN 01-170-7951 FY14 Demand Data Histogram

The fitted-Weibull data in Figure 128 shows a p-value of .22; therefore we cannot reject the hypothesis, "FY14 demand follows a Weibull distribution." Hence, for the second Monte Carlo simulation, we will use a Weibull distribution in conjunction with the parameters, scale = 72, shape = 1.59 and location = 0.

Fitted 2 parameter Weibull: FY-14 Demand for NIIN 011707951

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Scale	α	72.476118	36.885356	136.94423
Shape	β	1.5899155	0.720783	2.9419617

-2log(Likelihood) = 60.6756074392705

Goodness-of-Fit Test

Cramer-von Mises W Test

W-Square	Prob>W^2
0.072654	0.2211

Note: Ho = The data is from the Weibull distribution. Small p-values reject Ho.

Diagnostic Plot

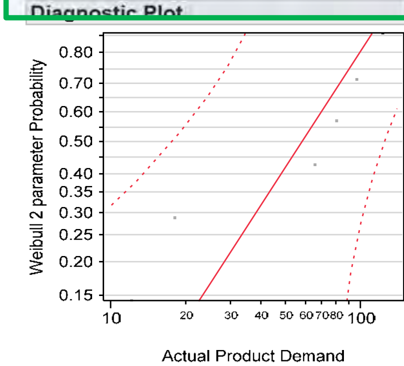


Figure 128. NIIN 01-170-7951 FY 14 Goodness-Of-Fit-Tests

The second Monte Carlo forecasts are depicted in Figures 129 and 130.

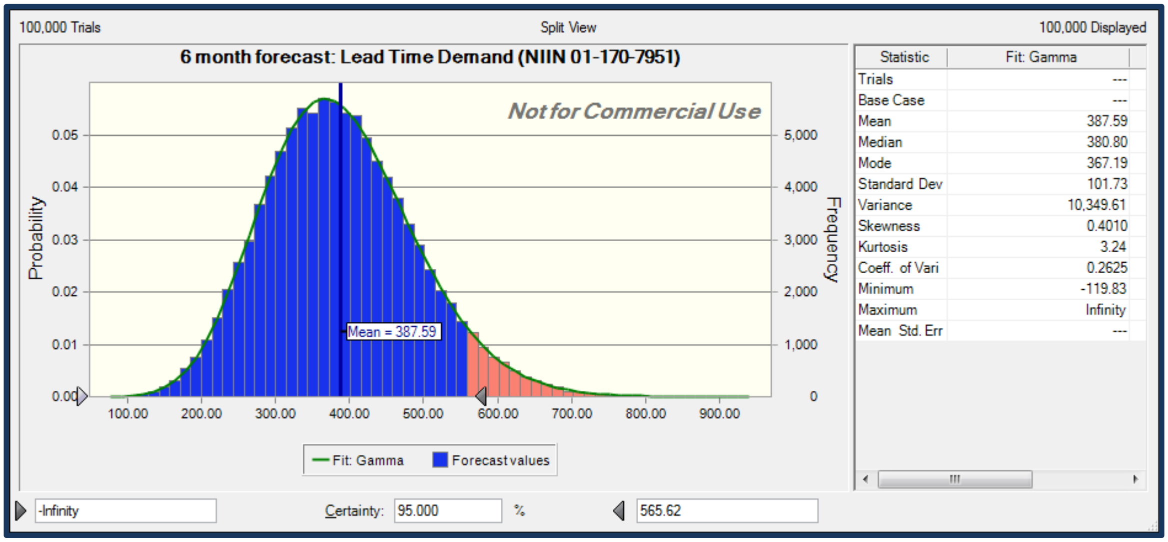


Figure 129. NIIN 01-170-7951 6-Month Forecast Simulation (2nd)

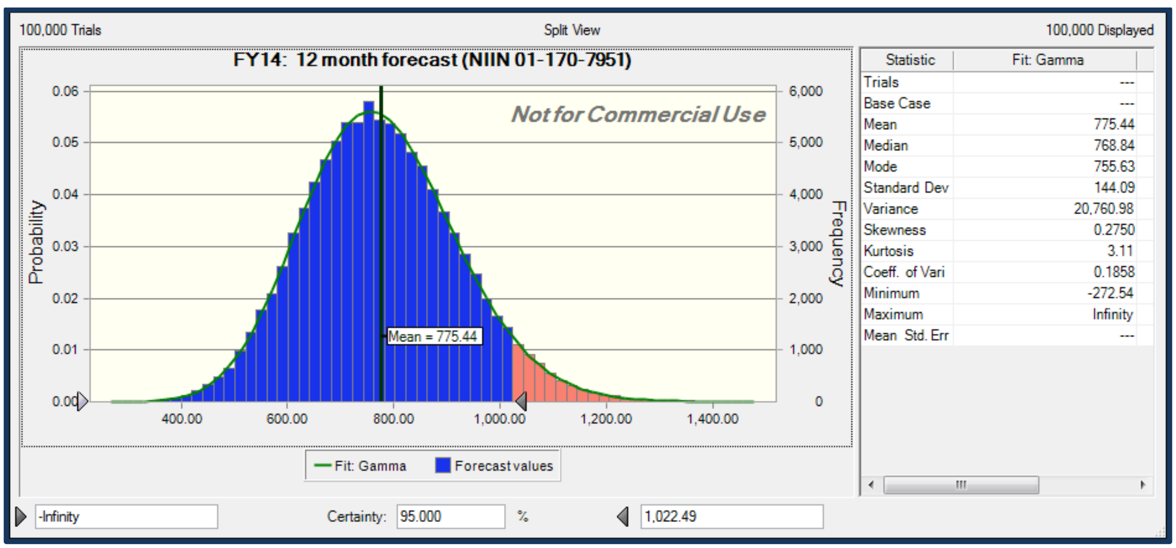


Figure 130. NIIN 01-170-7951 12-Month Forecast Simulation (2nd)

- **Observations from the Second Forecast**

In Figure 131, the 2013 October forecast error is 29%, whereas the 2014 April forecast error is 0%. If the April 2014 forecast was used to formulate inventory policy,

DLA would realize inventory cost reductions, because the actual inventory is high (see inventory-policy section below).

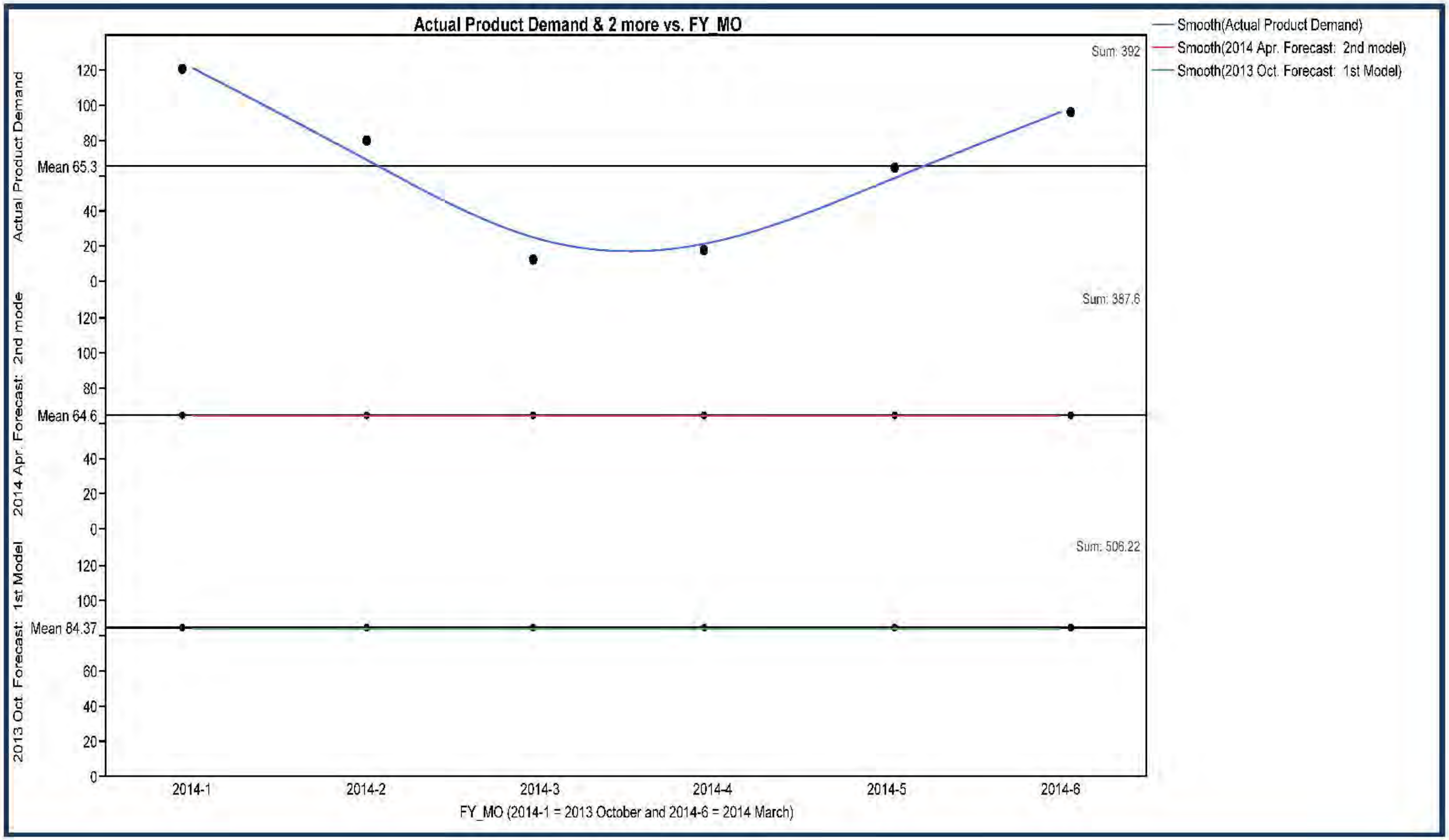


Figure 131. NIIN 01-170-7951 Monte Carlo Forecast Model versus Actual FY 14 Demand

Table 30 shows the improved forecast accuracy from 29% (Oct. 2013 model) to 0% (Apr. 2014 model).

	Six Month Forecast: Comparison of the forecast model vs. actual demand		
		Average	Average
FY_MO	**Actual Product Demand**	**Forecast: 1st model**	**Forecast: 2nd model**
2014-1	121	84.37	64.60
2014-2	80	84.37	64.60
2014-3	12	84.37	64.60
2014-4	18	84.37	64.60
2014-5	65	84.37	64.60
2014-6	96	84.37	64.60
Total	**392**	**506.24**	**387.59**
		Oct. 2013 six month forecast error:	
Delta forecast #1	114.24	ABS(506-392)/392 = ***29%***	Apr. 2014 six month forecast error:
Delta forecast #2	4.41		error: ABS(392-388)/392 = **0%**
All forecasts:			
FY 2014, six months:		506.24	388
FY 2014, twelve months:		1013	775
Lead Time demand, 6 months:		***506***	***388***
Reorder Point:		723	566

The market for this product is non-static, characterized by shifting conditions.
The Apr-14 forecast used months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.

Table 30. NIIN 01-170-7951 Comparison Second Forecast versus Actual Demand

D. INVENTORY-POLICY FORMULATION: AS CONDITIONS CHANGE, SO MUST INVENTORY POLICY

Table 31 shows the results of the Monte Carlo simulation results and guidance for inventory-policy change. Whereas DLA inventory policy for FY14 set the reorder point at 963 units, the April 2014 forecast called for a reorder point of 566 units. That is a difference of 397 units. At a FY14 price of about $233 per unit, the inventory cost reduction could be $92 thousand (selling price used in lieu of cost).

Evolving Inventory Policy: Narrowing the gap beween the model and the real world			
	Actual DLA QTY	1st forecast	**2nd forecast**
Effective date:	**FY 14**	Oct-13	**Apr-14**
Forecast		506	**388**
Safety Stock:	**247**	217	**178**
Reorder Point:	**963**	723	**566**
The market for this product is non-static, characterized by shifting conditions and uncertainty. The Apr-14 forecast used 6 months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.			
FY-14 unit price	Delta	**cost savings**	**cost increase**
$233	397	**$92,414**	

Table 31. NIIN 01-170-7951 Forecast Model versus Real World Demand

- **Inventory-Management Assumption**

This NIIN is mistakenly classified as a class-A item (see Chapter III for inventory classification). The outlier demand value of over 76 thousand units in March 2013 caused this NIIN to rise (erroneously) to class-A status. Therefore, it should be removed from the class-A list and managed with a periodic inventory policy, due to this product's low impact on (potential) overall annual revenue.

JMP software training (online) provides the insight, "All [forecast] models are wrong, but some are useful… The illustration below, Figure 132 states that the organization's performance is a function of their learning curve." See how this statement applies to inventory policy formulation in the next section as it discusses the cost reduction benefit of reducing lead time.

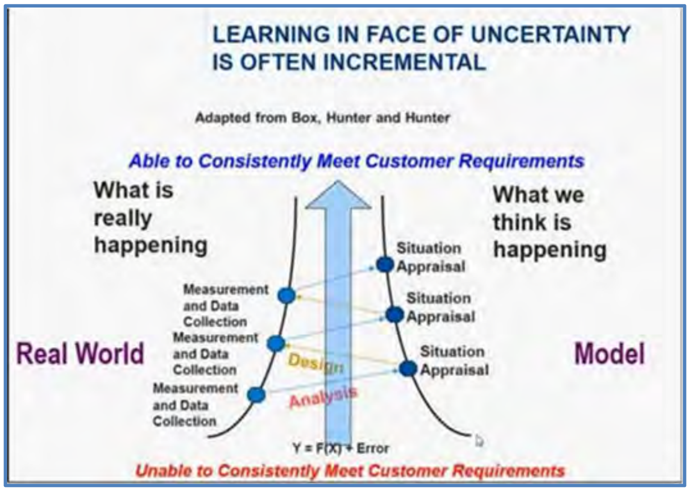


Figure 132. Learning curve, adopted from Exploring Best Practices in Design of Experiments SAS Institute (Webinar 2014)

E. CONDITIONAL-VALUE-AT-RISK ANALYSIS

The graph in Figure 133 shows the lead-time demand forecast. The 95% service level is shaded blue, and the value of this area under the demand curve is 566 units. The remaining 5% is the conditional value at risk (at the right tail of the distribution curve). Figure 134 represents the range of values of the conditional value at risk. The question arises, if stock runs out, what is the expected shortage quantity?

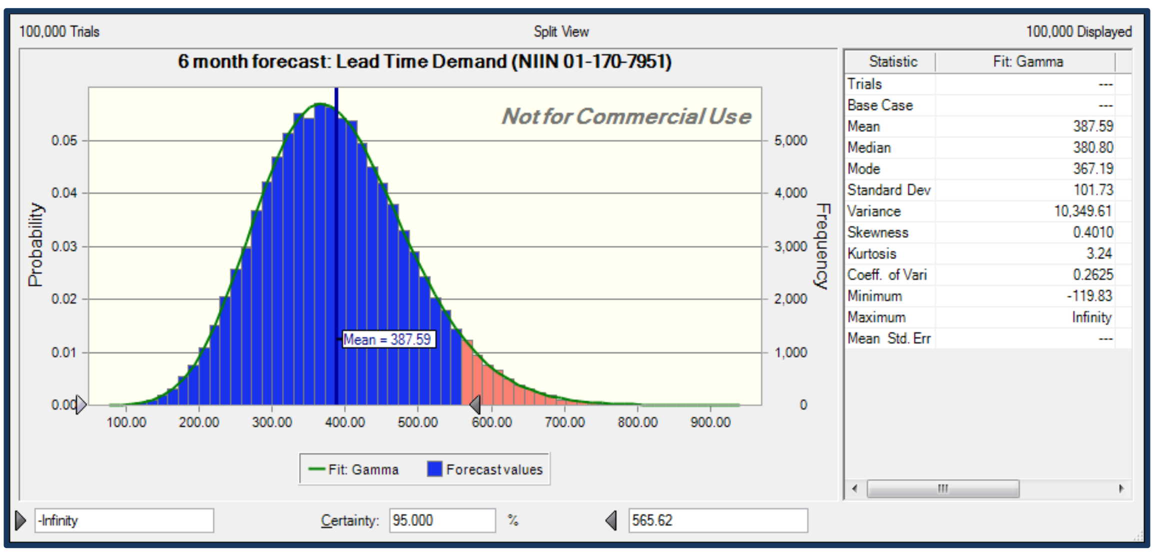


Figure 133. NIIN 01-170-7951 Lead Time Demand Forecast

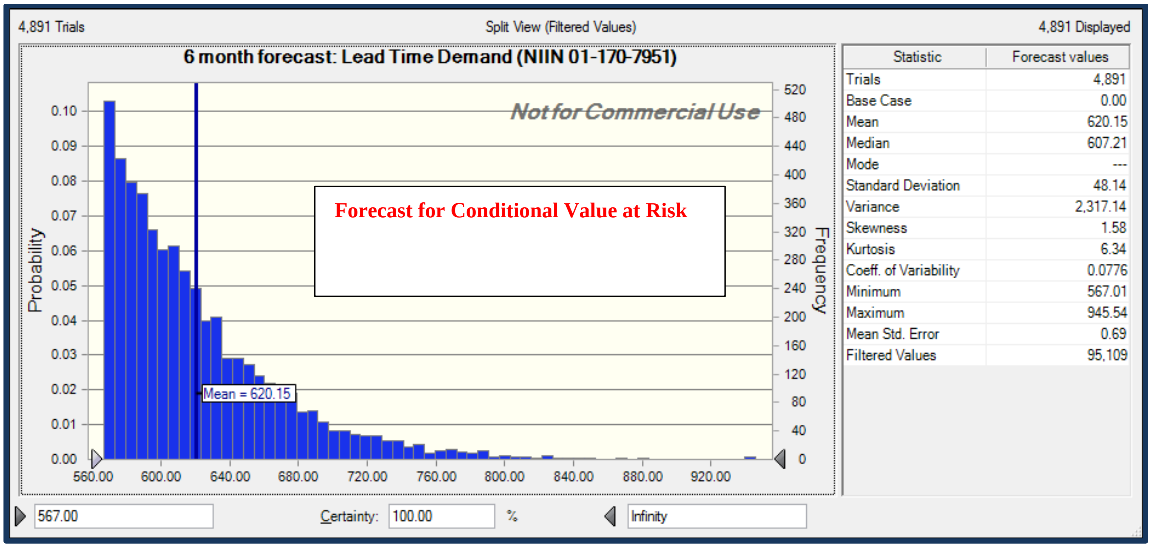


Figure 134. NIIN 01-170-7951 Conditional Value at Risk

The conclusions from the Monte Carlo simulation above are summarized in Table 32.

The average lead-time demand forecast (50% probability	**388 units** (lead time = 6 months)
A 95% fill rate quantity equals	**566 units** of inventory
Conditional risk: If demand exceeds stock on hand during the replenishment cycle, the expected shortage is	**620 units** (see forecast right tail distribution: 620 – 566 = 54)
How bad can things get if there is a stock out? The maximum shortage forecasted is	**5,530 units** (946 – 566 = 380).

Table 32. NIIN 01-170-7951 Lead Time Demand Forecast and Stock out Risk Analysis Summary Table

a. Improving the Organization's Learning Curve

The organization should produce demand forecasts and risk analysis for this NIIN on a quarterly basis at least and adjust the inventory policy (reorder point and safety stock

levels) as required. This implies integrated planning with the contracting officer and item manager for negotiating the right procurement contract with the supplier(s).

b. Learning-Curve Potential

Tables 33 and Figure 135 illustrate that lead time for this NIIN is 170 days (or about six months). Reducing the replenishment lead time (admin + procurement) would reduce the exposure period of demand uncertainty and would likely lead to lower safety stock and reorder points, and thus, lower inventory costs.

Lead Time (FY-14)	
procurement lead time days:	155
admin lead time days:	15
total days:	170
months	**5.7**

Table 33. NIIN 01-170-7951 Admin and Procurement Lead Time

Tabulate

FY	FY_MO	FY_MO Series	Calendar Month	niin	itm_name	std_u_price	qty_req Sum	Revenue Sum	alt 10	alt 15	alt 70	alt 90	alt 120	plt 155	plt 180
2010	2010_1	1	10	011707951	FAIRING,AIRCRAFT	$146.16	102	$14,908.32	0	0	0	0	5	0	5
	2010_2	2	11	011707951	FAIRING,AIRCRAFT	$146.16	91	$13,300.56	0	0	0	0	6	0	6
	2010_3	3	12	011707951	FAIRING,AIRCRAFT	$146.16	42	$6,138.72	0	0	0	0	3	0	3
	2010_4	4	1	011707951	FAIRING,AIRCRAFT	$146.16	54	$7,892.64	0	0	0	0	6	0	6
	2010_5	5	2	011707951	FAIRING,AIRCRAFT	$146.16	66	$9,646.56	0	0	0	0	5	0	5
	2010_6	6	3	011707951	FAIRING,AIRCRAFT	$146.16	105	$15,346.80	0	0	0	0	6	0	6
	2010_7	7	4	011707951	FAIRING,AIRCRAFT	$146.16	136	$19,877.76	0	0	0	0	9	0	9
	2010_8	8	5	011707951	FAIRING,AIRCRAFT	$146.16	103	$15,054.48	0	0	0	0	8	0	8
	2010_9	9	6	011707951	FAIRING,AIRCRAFT	$146.16	99	$14,469.84	0	0	0	0	8	0	8
	2010_10	10	7	011707951	FAIRING,AIRCRAFT	$219.07	62	$13,582.34	0	0	0	0	6	0	6
	2010_11	11	8	011707951	FAIRING,AIRCRAFT	$219.07	106	$23,221.42	0	0	0	0	6	0	6
	2010_12	12	9	011707951	FAIRING,AIRCRAFT	$219.07	65	$14,239.55	0	0	0	0	4	0	4
2011	2011_1	1	10	011707951	FAIRING,AIRCRAFT	$219.07	68	$14,896.76	0	0	0	0	3	0	3
	2011_2	2	11	011707951	FAIRING,AIRCRAFT	$219.07	25	$5,476.75	0	0	0	0	4	0	4
	2011_3	3	12	011707951	FAIRING,AIRCRAFT	$219.07	22	$4,819.54	0	0	0	0	3	0	3
	2011_4	4	1	011707951	FAIRING,AIRCRAFT	$219.07	46	$10,077.22	0	0	0	0	4	0	4
	2011_5	5	2	011707951	FAIRING,AIRCRAFT	$219.07	83	$18,182.81	0	0	0	0	6	0	6
	2011_6	6	3	011707951	FAIRING,AIRCRAFT	$219.07	192	$42,061.44	0	0	0	0	4	0	4
	2011_7	7	4	011707951	FAIRING,AIRCRAFT	$219.07	250	$54,767.50	0	0	0	0	7	0	7
	2011_8	8	5	011707951	FAIRING,AIRCRAFT	$219.07	64	$14,020.48	0	0	0	0	3	0	3
	2011_9	9	6	011707951	FAIRING,AIRCRAFT	$219.07	109	$23,878.63	0	0	0	0	6	0	6
	2011_10	10	7	011707951	FAIRING,AIRCRAFT	$222.09	88	$19,543.92	0	0	0	0	8	0	8
	2011_11	11	8	011707951	FAIRING,AIRCRAFT	$222.09	91	$20,210.19	0	0	0	0	9	0	9
	2011_12	12	9	011707951	FAIRING,AIRCRAFT	$222.09	157	$34,868.13	0	0	0	0	10	0	10
2012	2012_1	1	10	011707951	FAIRING,AIRCRAFT	$222.09	130	$28,871.70	0	0	0	0	7	0	7
	2012_2	2	11	011707951	FAIRING,AIRCRAFT	$222.09	166	$36,866.94	0	0	0	0	6	0	6
	2012_3	3	12	011707951	FAIRING,AIRCRAFT	$222.09	20	$4,441.80	0	0	0	0	4	0	4
	2012_4	4	1	011707951	FAIRING,AIRCRAFT	$214.32	77	$16,502.64	0	8	0	0	0	0	8
	2012_5	5	2	011707951	FAIRING,AIRCRAFT	$214.32	81	$17,359.92	0	7	0	0	0	0	7
	2012_6	6	3	011707951	FAIRING,AIRCRAFT	$214.32	133	$28,504.56	0	7	0	0	0	0	7
	2012_7	7	4	011707951	FAIRING,AIRCRAFT	$214.32	102	$21,860.64	0	9	0	0	0	0	9
	2012_8	8	5	011707951	FAIRING,AIRCRAFT	$214.32	56	$12,001.92	0	6	0	0	0	0	6
	2012_9	9	6	011707951	FAIRING,AIRCRAFT	$214.32	96	$20,574.72	0	7	0	0	0	0	7
	2012_10	10	7	011707951	FAIRING,AIRCRAFT	$215.30	75	$16,147.50	0	10	0	0	0	0	10
	2012_11	11	8	011707951	FAIRING,AIRCRAFT	$215.30	134	$28,850.20	0	12	0	0	0	0	12
	2012_12	12	9	011707951	FAIRING,AIRCRAFT	$215.30	95	$20,453.50	0	10	0	0	0	0	10
2013	2013_1	1	10	011707951	FAIRING,AIRCRAFT	$215.30	74	$15,932.20	8	0	0	0	0	0	8
	2013_2	2	11	011707951	FAIRING,AIRCRAFT	$215.30	131	$28,204.30	7	0	0	0	0	0	7
	2013_3	3	12	011707951	FAIRING,AIRCRAFT	$215.30	35	$7,535.50	6	0	0	0	0	0	6
	2013_4	4	1	011707951	FAIRING,AIRCRAFT	$215.30	105	$22,606.50	8	0	0	0	0	0	8
	2013_5	5	2	011707951	FAIRING,AIRCRAFT	$215.30	121	$26,051.30	7	0	0	0	0	0	7
	2013_6	6	3	011707951	FAIRING,AIRCRAFT	$215.30	76,390	$16,446,767.00	9	0	0	0	0	0	9
	2013_7	7	4	011707951	FAIRING,AIRCRAFT	$215.30	180	$38,754.00	0	0	0	10	0	0	10
	2013_8	8	5	011707951	FAIRING,AIRCRAFT	$215.30	29	$6,243.70	0	0	0	4	0	0	4
	2013_9	9	6	011707951	FAIRING,AIRCRAFT	$215.30	189	$40,691.70	0	0	0	7	0	0	7
	2013_10	10	7	011707951	FAIRING,AIRCRAFT	$232.78	128	$29,795.84	0	0	8	0	0	0	8
	2013_11	11	8	011707951	FAIRING,AIRCRAFT	$232.78	77	$17,924.06	0	0	5	0	0	0	5
	2013_12	12	9	011707951	FAIRING,AIRCRAFT	$232.78	92	$21,415.76	0	0	7	0	0	0	7
2014	2014_1	1	10	011707951	FAIRING,AIRCRAFT	$232.78	121	$28,166.38	0	5	0	0	0	5	0
	2014_2	2	11	011707951	FAIRING,AIRCRAFT	$232.78	80	$18,622.40	0	7	0	0	0	7	0
	2014_3	3	12	011707951	FAIRING,AIRCRAFT	$232.78	12	$2,793.36	0	3	0	0	0	3	0
	2014_4	4	1	011707951	FAIRING,AIRCRAFT	$232.78	18	$4,190.04	0	5	0	0	0	5	0
	2014_5	5	2	011707951	FAIRING,AIRCRAFT	$232.78	65	$15,130.70	0	7	0	0	0	7	0
	2014_6	6	3	011707951	FAIRING,AIRCRAFT	$232.78	96	$22,346.88	0	6	0	0	0	6	0

Figure 135. NIIN 01-170-7951 Monthly Demand, Admin Lead Time and Production Lead Time

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APPENDIX E. PRODUCT-DEMAND FORECAST FOR NIIN 011707951 TURBINE-ENGINE PARTS KIT

Information found in this section regarding product demand forecast for the parts kit of the turbine engine includes:

A. Statistical analysis of product demand

B. Observations from the statistical analysis

C. Lead-time-demand forecast: an input for inventory policy

D. Inventory-policy formulation

E. Conditional-value-at-risk analysis

A. STATISTICAL ANALYSIS OF PRODUCT DEMAND

Demand for the parts kit was variable from FY10 to FY13. Note the two outlier values as shown in Figure 136, 110 units in October 2010 (FY_MO 2010–1) and 60 units in June 2012 (FY_MO 2012–9) which dominate demand during this period. “Dominates” is used to mean that these outlier values unduly pull upward the average monthly demand for this product (up to 22 units per month).

Two outlier values were excluded from Figure 137: QTY = 110 in October 2010 and QTY = 60 in June 2012. Notice the decrease in mean value from 22 units to 19 units (rounded). This graph helps to visualize the monthly demand variability across time from FY10 – FY13. The general trend is small decreases in demand across succeeding fiscal years, starting in FY10. Figures 138 and 139 depict the trend of decreased (mean) demand across fiscal years.

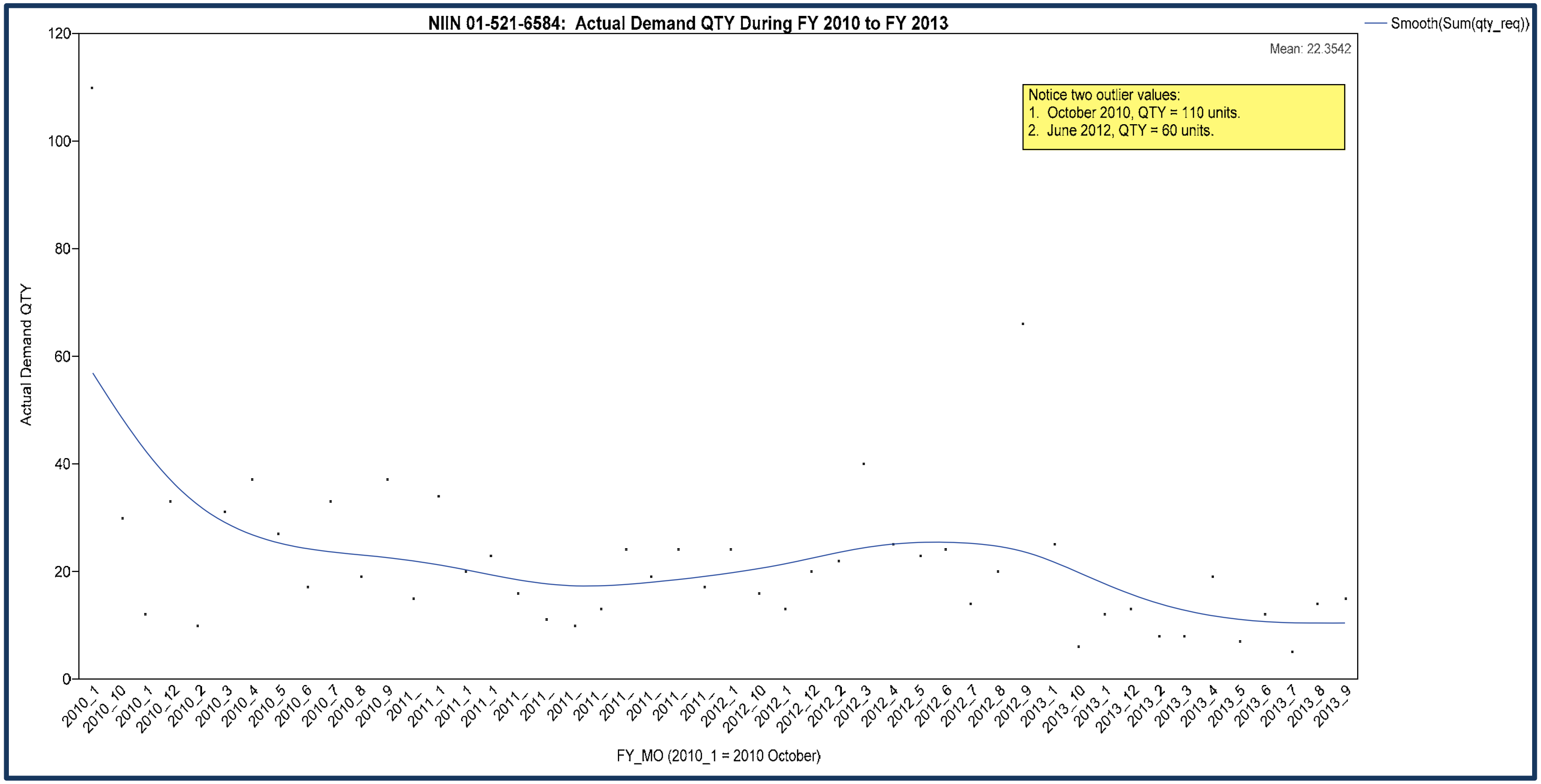


Figure 136. NIIN 01-521-6584 Monthly Demand FY 10 – FY 13

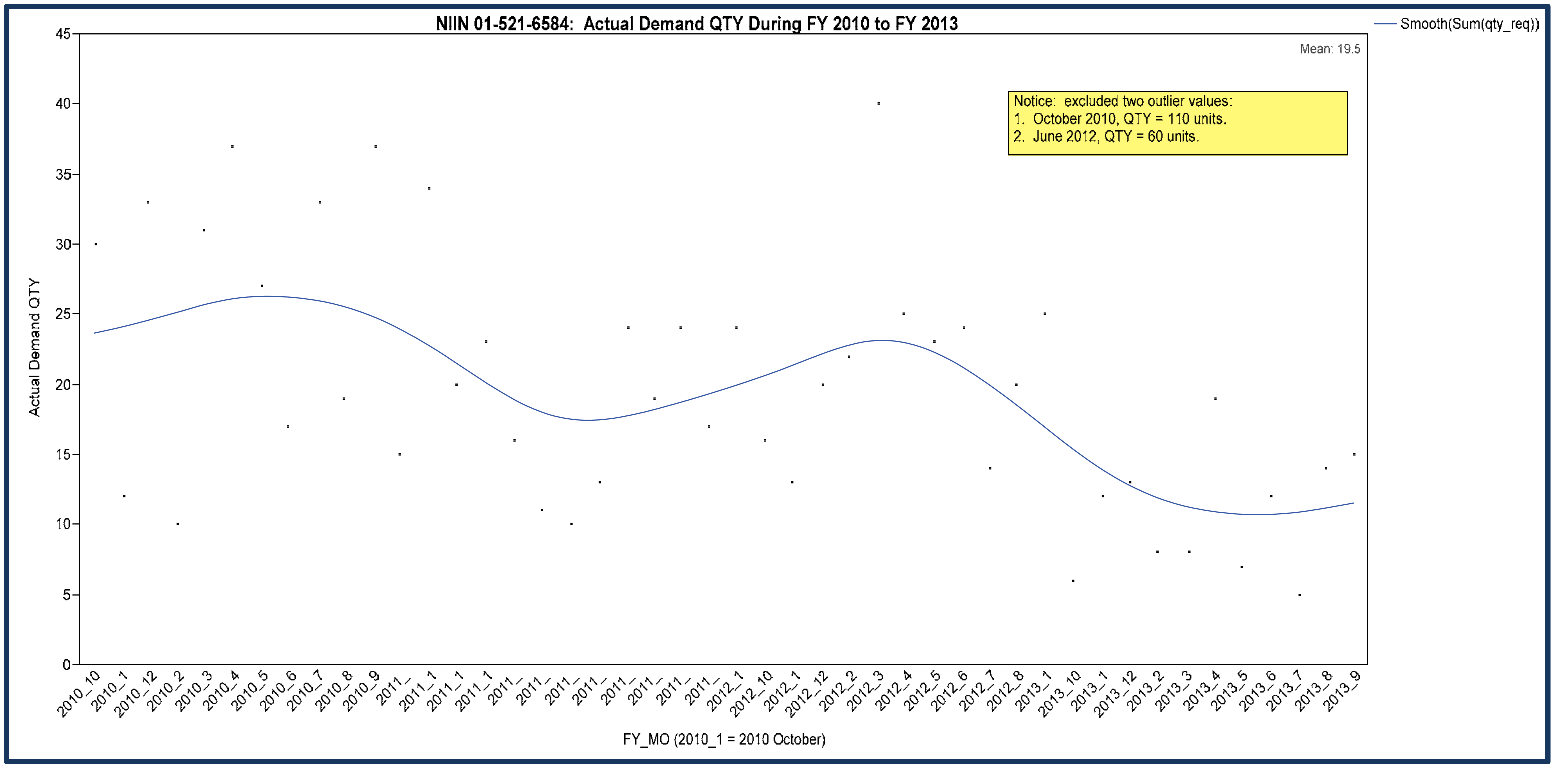


Figure 137. NIIN 01-521-6584 Monthly Demand FY10 - FY13 without Outlier

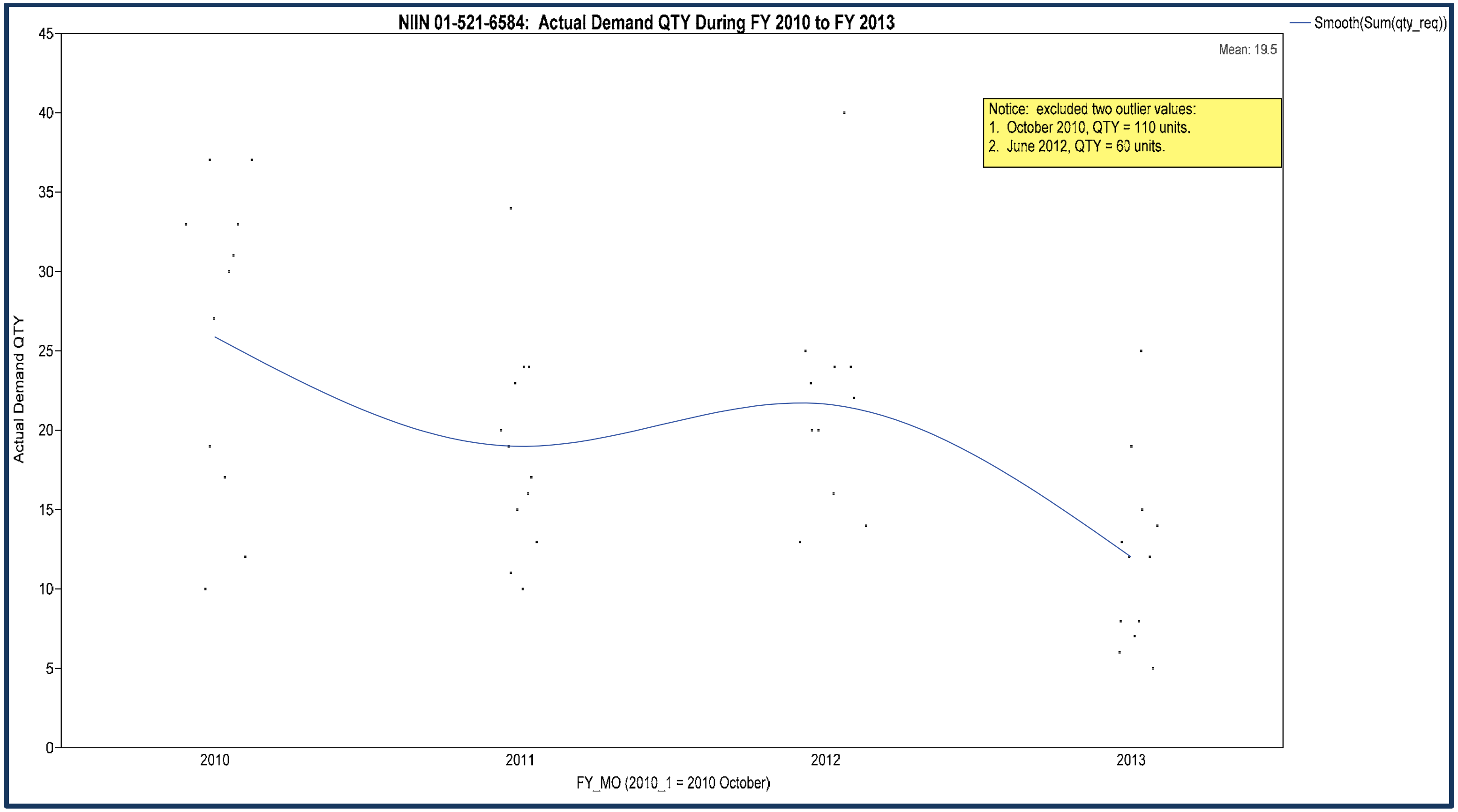


Figure 138. NIIN 01-521-6584 Demand History FY10 – FY13 (A)

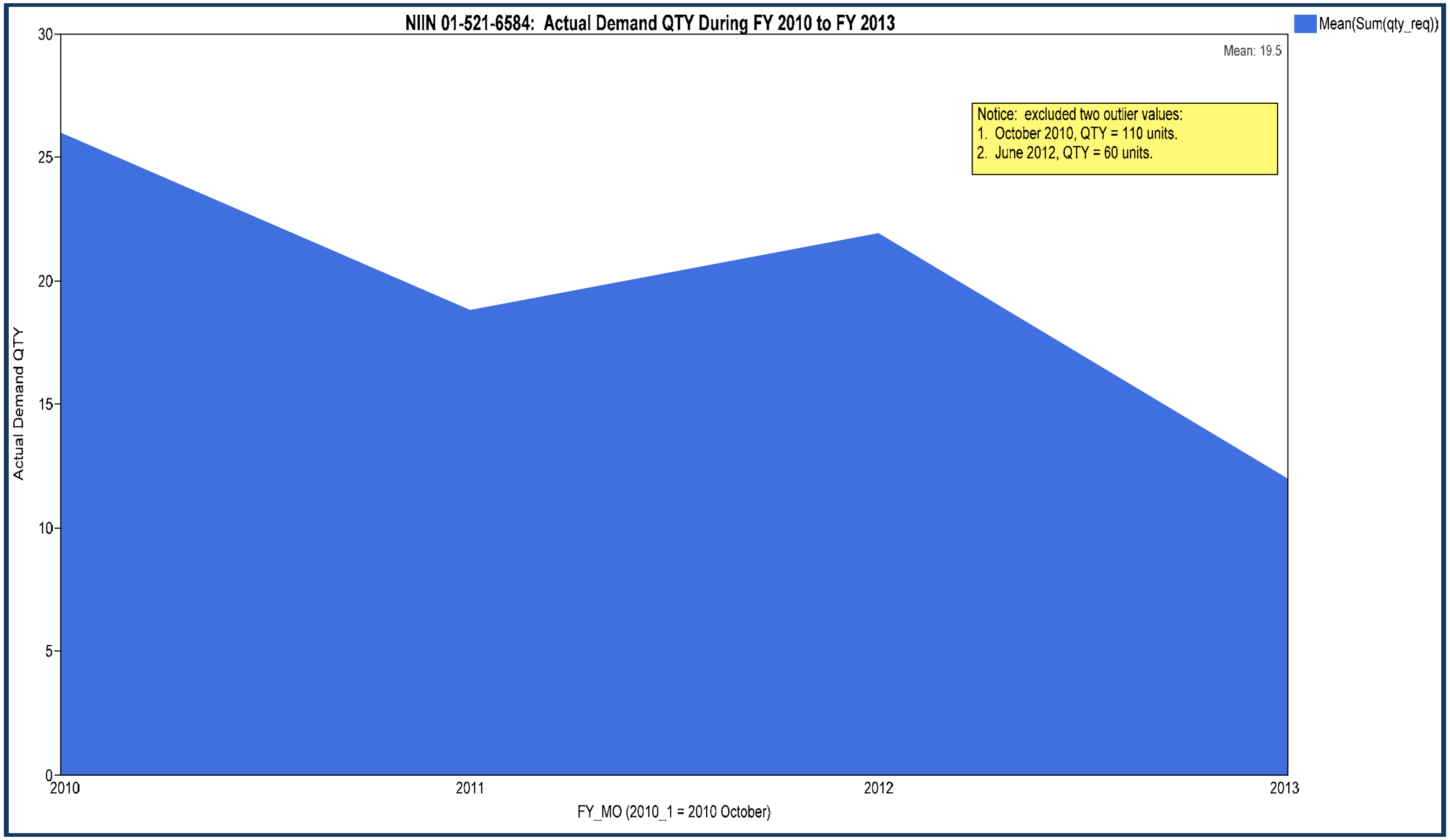
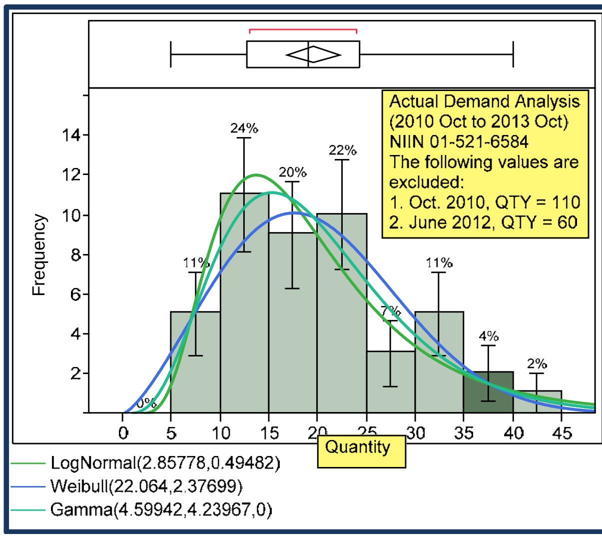


Figure 139. NIIN 01-521-6584 Demand History FY10 – FY13 (B)

- **Probability Distribution Analysis**

Various probability distributions have been fit to the demand data (FY10–FY13). The Weibull distribution appears to have the best goodness of fit (highest p-value) across most fiscal years; therefore, our hypothesis is, "monthly demand follows a Weibull distribution."

In the histogram in Figure 140, the outlier values (from October 2010 and June 2012) are not included. The highest monthly demand value is QTY = 40 units and the mean value is 19.5 units. We are searching for a useful range of values of product demand; therefore, we must avoid using overinflated values for our forecast model.



Quantiles

100.0%	maximum	40
99.5%		40
97.5%		39.475
90.0%		33.3
75.0%	quartile	24.25
50.0%	median	19
25.0%	quartile	12.75
10.0%		8
2.5%		5.175
0.5%		5
0.0%	minimum	5

Summary Statistics

Mean	19.5
Std Dev	8.9187692
Std Err Mean	1.3150008
Upper 95% Mean	22.148548
Lower 95% Mean	16.851452
N	46
Sum	897
Variance	79.544444
Skewness	0.5124325
Kurtosis	-0.451166
Median	19
Mode	24
Range	35
Interquartile Range	11.5

Figure 140. NIIN 01-521-6584 Demand Data Histogram

JMP software used the product demand range from the histogram above to generate the prediction-interval section in the green box in Figure 141. The lower–upper ranges in both the mean (μ) value and standard deviation are relatively large. Recall that a decreasing trend seems to dominate the pattern of product demand from FY10–FY13. Therefore, the lower mean confidence level for monthly demand could be the more valid predictor value for our forecast model (μ = 11.7 units).

Prediction Interval

Parameter	Future N	Lower PI	Upper PI	1-Alpha
Individual	6	-5.38129	44.38129	0.950
Mean	6	11.70289	27.29711	0.950
Std Dev	6	3.594169	15.09357	0.950

Compare Distributions

Show	Distribution	Number of Parameters	-2*LogLikelihood	AICc
☑	Gamma	2	326.589148	330.868217
☑	Weibull	2	326.904366	331.183436
☐	Extreme Value	2	326.904366	331.183436
☑	LogNormal	2	328.731592	333.010662
☐	Johnson Sl	3	327.265573	333.837001
☐	Normal	2	330.852877	335.131947
☐	GLog	3	328.731592	335.303021
☐	Johnson Su	4	327.265573	336.241182
☐	Normal 2 Mixture	5	325.922492	337.422492
☐	Normal 3 Mixture	8	320.958934	340.850826
☐	Exponential	1	365.278131	367.36904

Figure 141. NIIN 01-521-6584 Prediction Interval

See the fitted-Weibull section in the orange box in Figure 142 (Probability Distribution Analysis). Notice the P-value is .25; therefore, there is not enough evidence to reject the hypothesis that the demand data follows a Weibull distribution. The parameters in the fitted Weibull section are high (mean = 19.29 and shape = 1.87) and will not produce a forecast with a decreasing demand trend. Therefore, all things considered, we favor using the parameters from the prediction interval: scale (mean) = 11.7; shape = 3.59. The Weibull distribution forecast model requires a lower bound value (location); therefore, we will use zero (0).

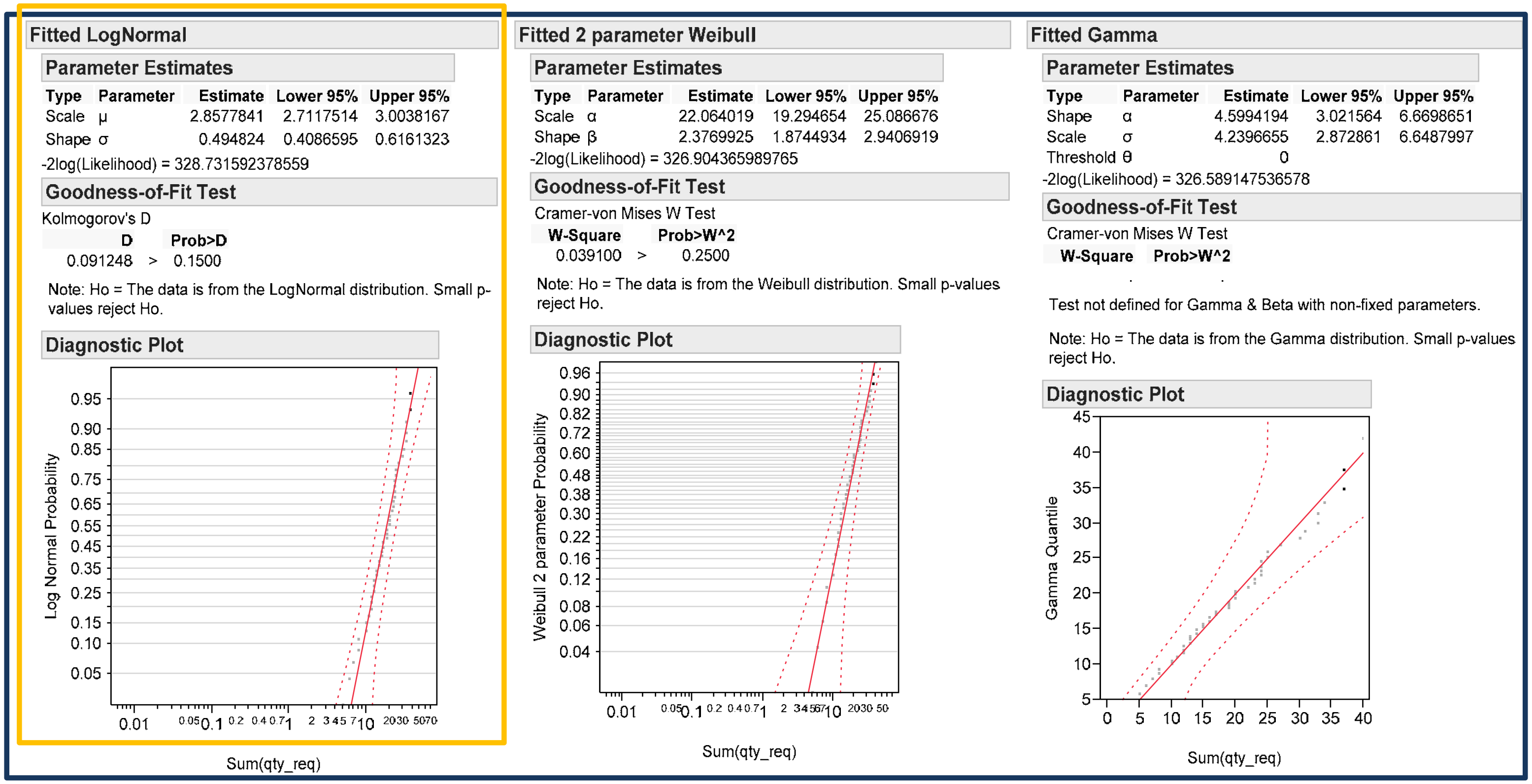


Figure 142. NIIN 01-521-6584 Goodness-of-Fit Tests

- **Time-Series Analysis of Demand**

Demand in each fiscal year is highly variable; however, the mean value and standard deviation are the strongest indicators of what demand quantity could be during the lead-time demand (demand between replenishment cycles).

The JMP time-series forecasts in Figures 143 – 146 provide a sensitivity analysis for the forecast models that we will build using Crystal Ball. Among these forecasts, the damped-trend exponential-smoothing forecast has the highest p-value (.73), which is higher (better) than the Weibull distribution p-value (.25).

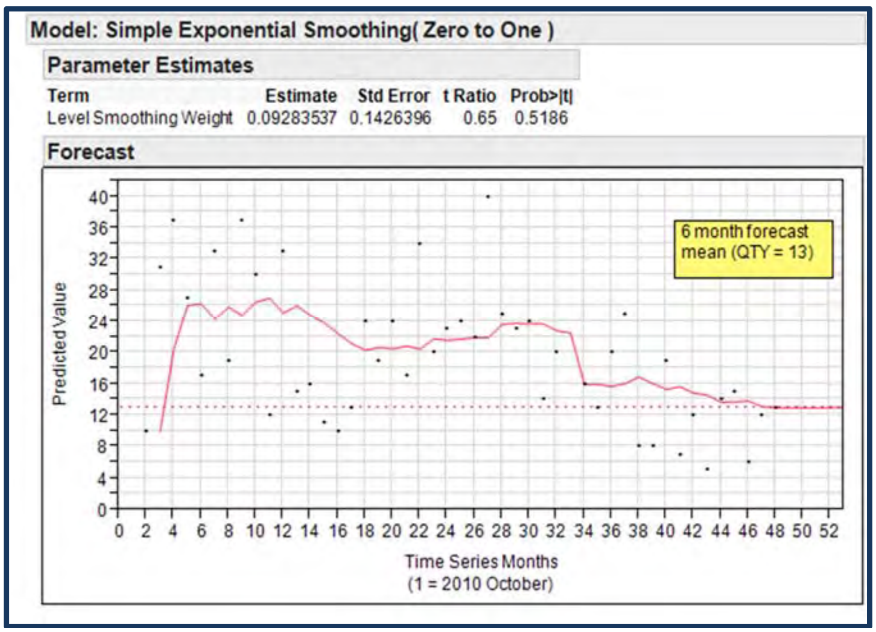


Figure 143. NIIN 01-521-6584 Simple Exponential Smoothing Forecast

Model: Damped-Trend Linear Exponential Smoothing

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.09283537	0.2747502	0.34	0.7372
Trend Smoothing Weight	0.99756489	.	.	.
Damping Smoothing Weight	0.00000000	.	.	.

Forecast

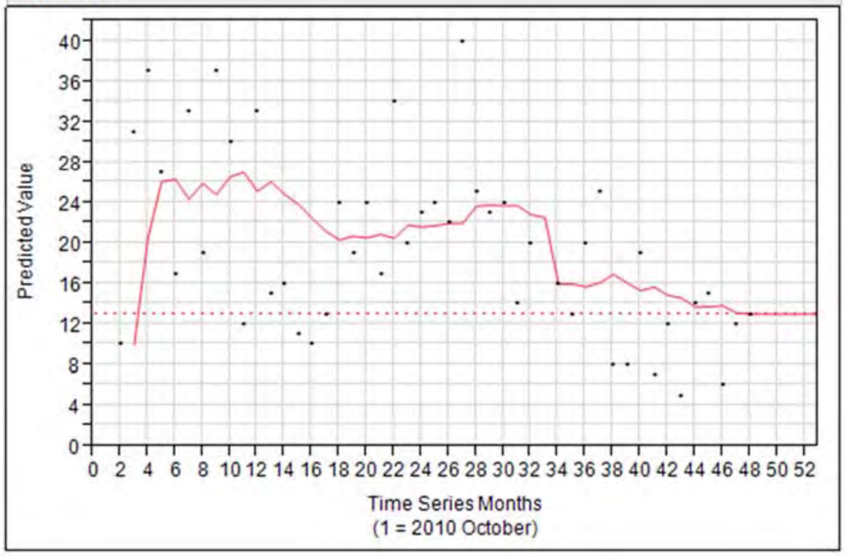


Figure 144. NIIN 01-521-6584 Damped-Trend, Linear Exponential Smoothing Forecast

Model: Double (Brown) Exponential Smoothing

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.21382854	0.0568088	3.76	0.0005*

Forecast

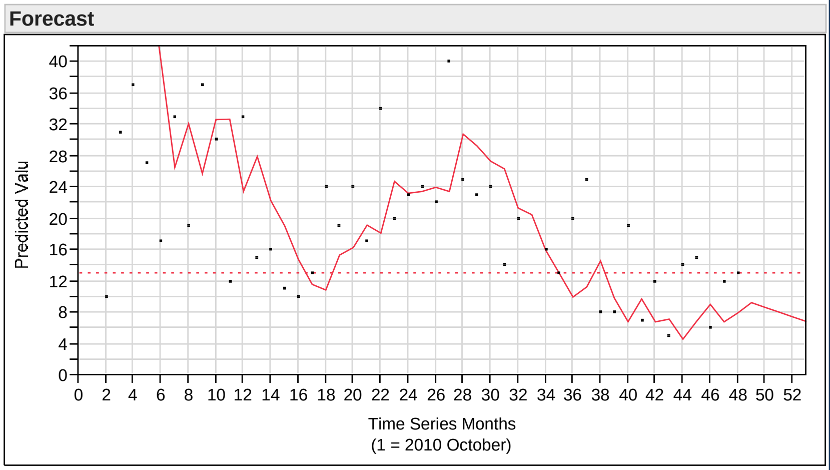


Figure 145. NIIN 01-521-6584 Brown Exponential Smoothing Forecast

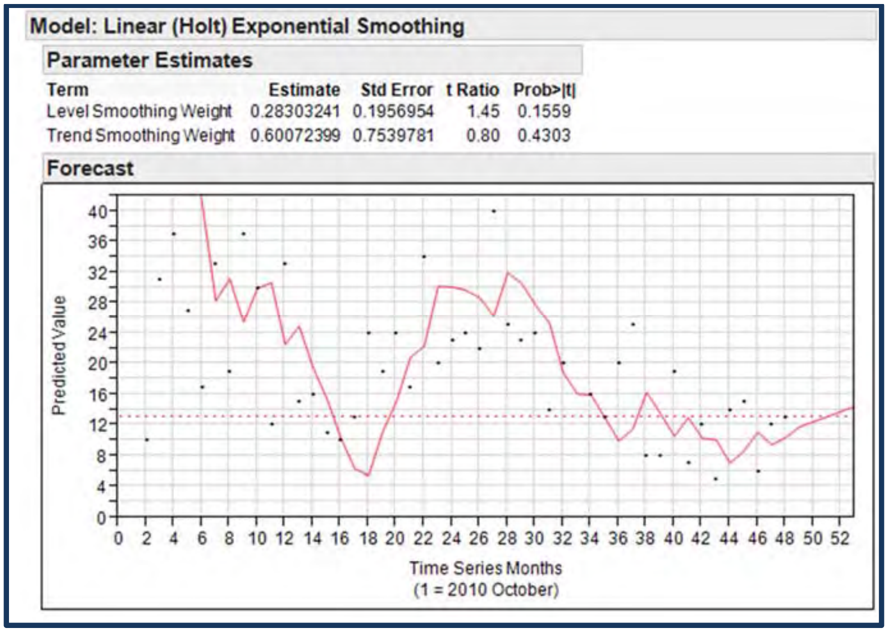


Figure 146. NIIN 01-521-6584 Liner (Holt) Exponential Smoothing Forecast

B. OBSERVATIONS FROM THE STATISTICAL ANALYSIS

According to the JMP statistical analysis, the demand for this NIIN appeared non-static and highly variable. Although no adequate probability distribution fit was found, the Weibull distribution had the highest p-value for a distribution fit.

C. LEAD-TIME DEMAND FORECAST (TWELVE MONTHS) USING THE MONTE CARLO SIMULATION

- **First Forecast**

It is assumed the forecast was conducted at the end of FY13. We used demand data from FY10 to FY13 as the representative time segment for predicting lead-time demand.

- Weibull distribution parameters for the Crystal Ball forecast model: scale = 11.7; shape = 3.59; location: 0.
- Lead-time demand during twelve months = 127 units.
- 95% fill rate = lead-time demand + safety stock = 145 units

The Monte Carlo simulations in Figures 147 and 148 show forecasts from twelve months (lead time) and six months (to gauge forecast model performance against the actual FY14 demand). Actual demand data for October 2013 to March 2014 was known. Therefore, we used the six-month forecast to gauge performance (that is, forecast error between the model and the real world).

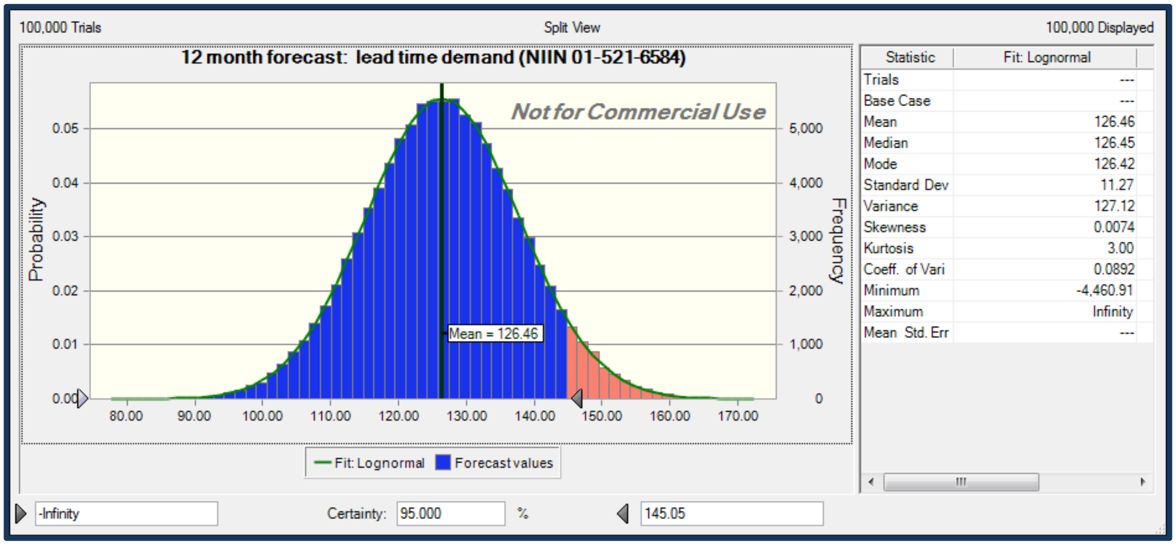


Figure 147. NIIN 01-521-6584 12-Month Forecast Simulation (1st)

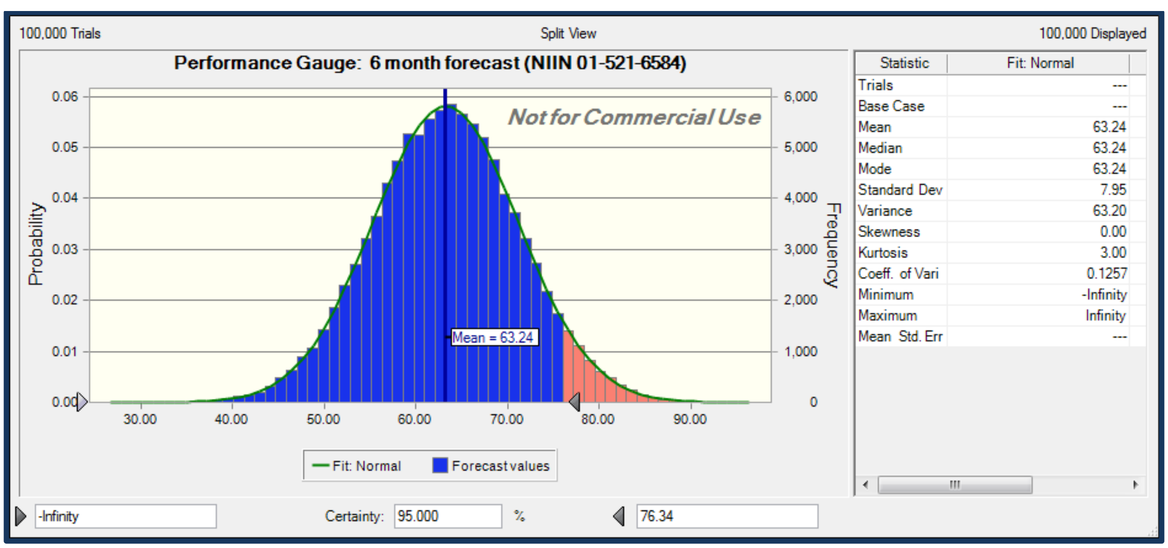


Figure 148. NIIN 01-521-6584 6-Month Forecast Simulation (1st)

- **Observations from the First Forecast**

It is assumed this observation was compiled after a six month lapse in March 2014. Figure 149 shows a forecast error of 31%, and if the forecast below was used to formulate inventory policy, DLA would realize an inventory cost reduction, because actual inventory is high (see April 2014 forecast and inventory-policy section below).

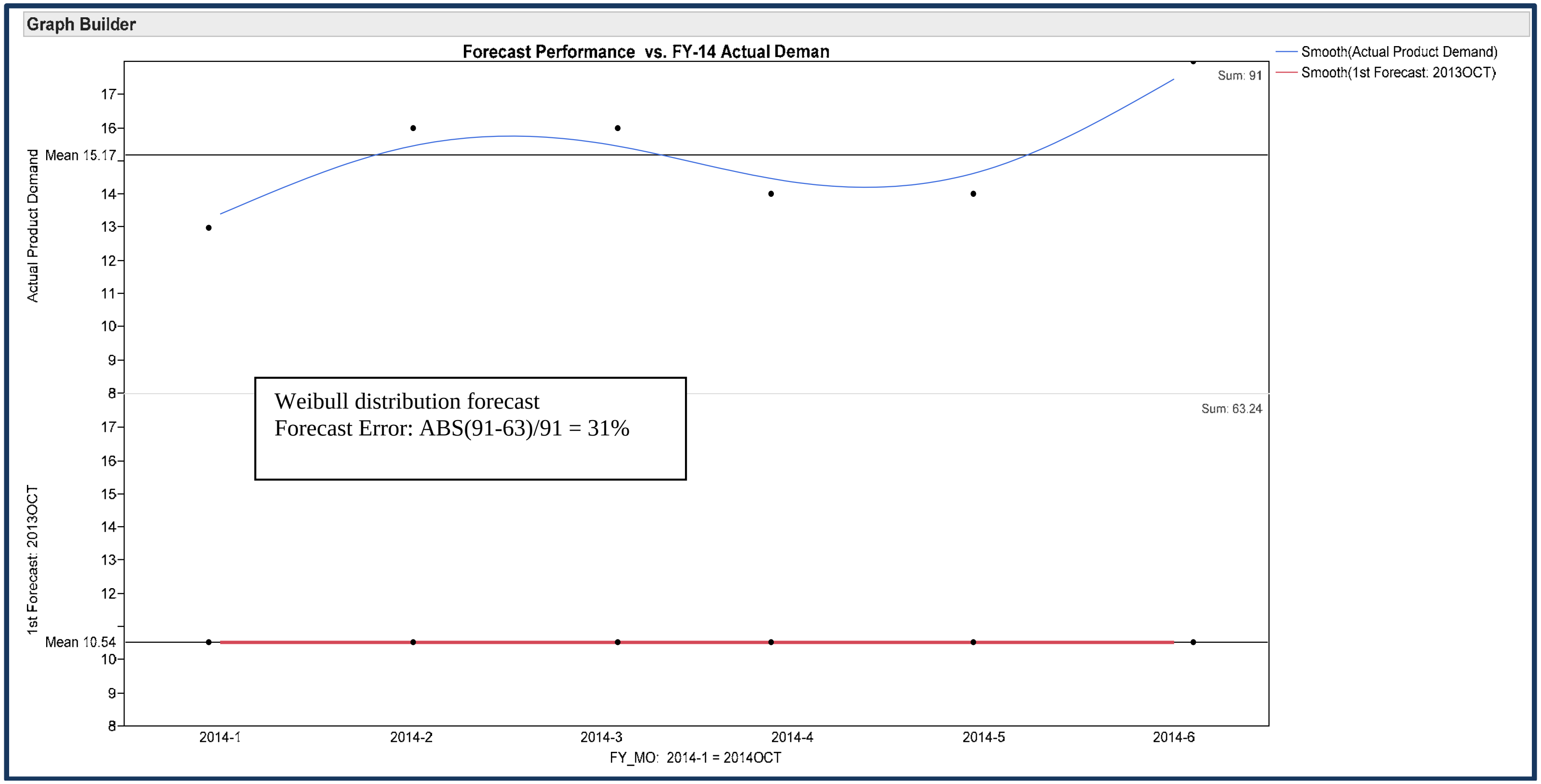


Figure 149. NIIN 01-521-6584 Monte Carlo Forecast Model versus Actual FY 14 Demand (31% error)

Table 34 compares the results of the first forecast with actual product demand during the first six months of FY14. The lead-time demand forecast is also provided (shaded gray). The forecast reorder point is 145 units. Caution: The forecast was too low; see the mid-year forecast (2014 April) and inventory-policy formulation for corrective. action.

Six Month Forecast: Comparison of the forecast model vs. actual demand

FY_MO	Actual Product Demand	Average Forecast: 1st model	Average Forecast: 2nd model
2014-1	13	10.54	
2014-2	16	10.54	
2014-3	16	10.54	
2014-4	14	10.54	
2014-5	14	10.54	
2014-6	18	10.54	
Total	**91**	**63.24**	**0**
		Oct. 2013 six month forecast error:	
Delta forecast #1	27.76	ABS(91-63)/91 = 31%	Apr. 2014 six month forecast error:

All forecasts:		
FY 2014, six months:	63	
FY 2014, twelve months:	127	
Lead Time demand, 12 months:	*127*	
Reorder Point:	145	

The market for this product is non-static, characterized by shifting conditions.

Table 34. NIIN 01-521-6584 Comparison First Forecast versus Actual Demand

- **Second Forecast**

It is assumed this forecast was conducted on the first week of April 2014 (that is, as a mid-year forecast). We continued to use the Weibull distribution, but changed the parameters: scale = 15.93 and shape 9.57 (see fitted-Weibull analysis of FY14 demand in Figure 150).

Again, we used FY14 QTR 1 and QTR 2 demand data to gauge forecast-model performance.

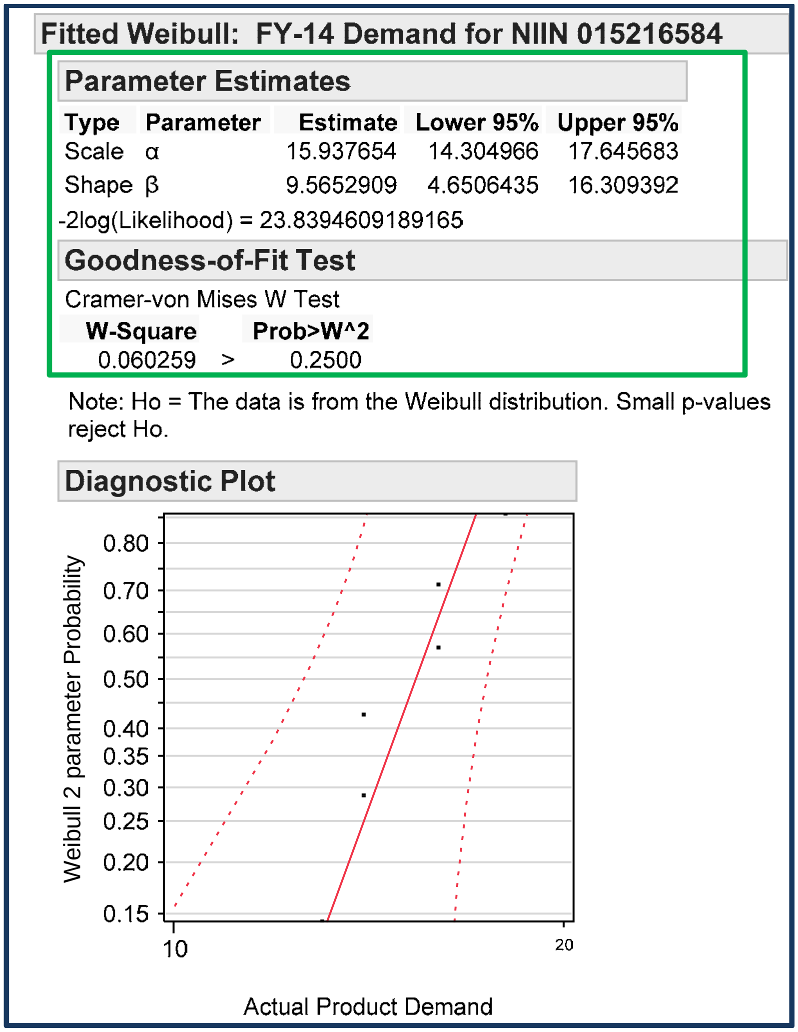


Figure 150. NIIN 01-521-6584 FY 14 Goodness of Fit Test

The forecasts are presented in Figures 151 and 152.

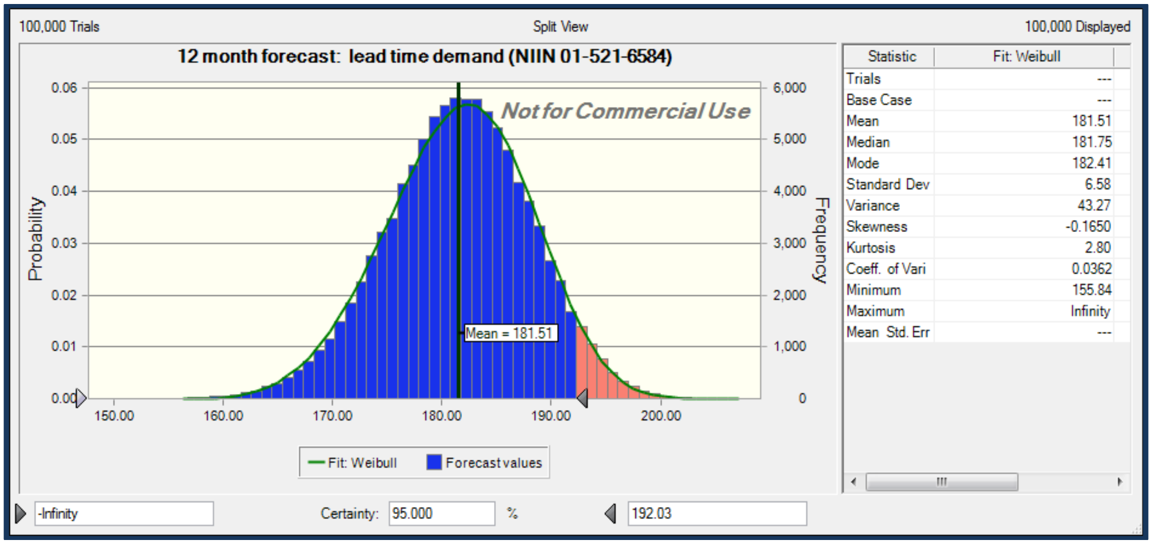


Figure 151. NIIN 01-521-6584 12-Month Forecast Simulation (2nd) .

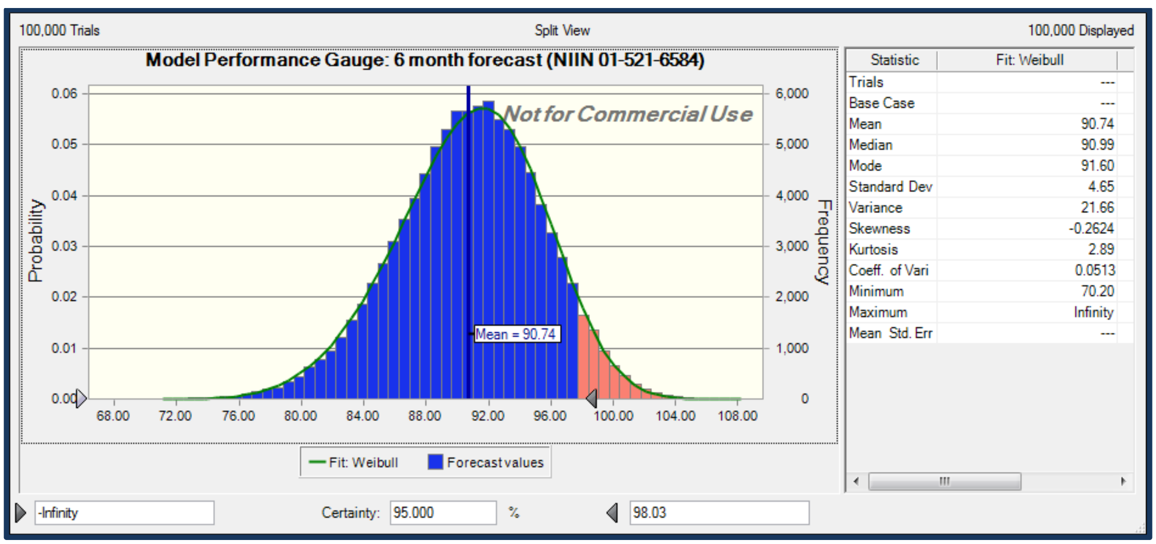


Figure 152. NIIN 01-521-6584 6-Month Forecast Simulation (2nd)

- **Observations from the Second Forecast**

Figure 153 shows a forecast error of 0%. If the forecast was used to formulate inventory policy, DLA could significantly reduce inventory costs, because the actual inventory is high.

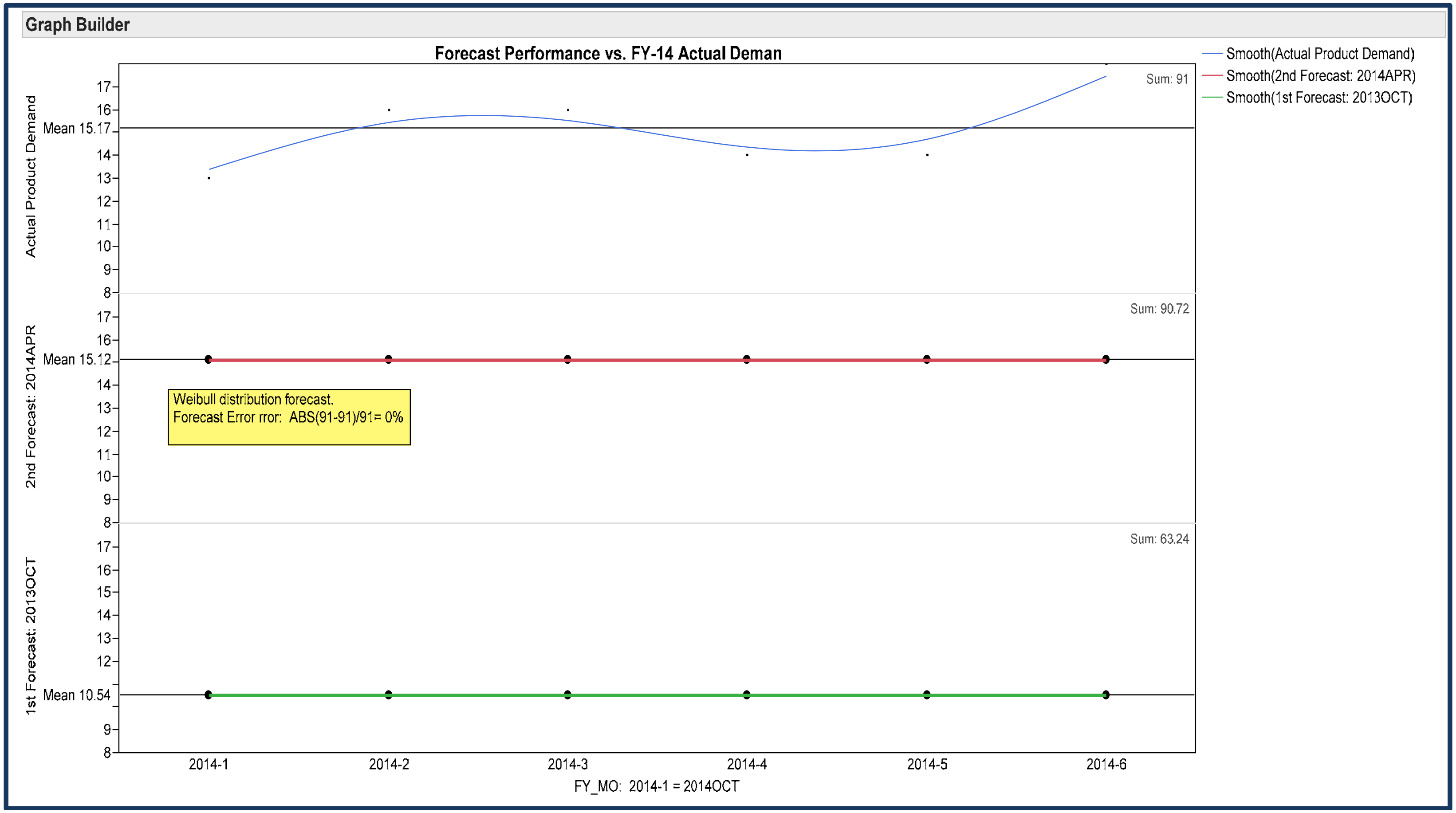


Figure 153. NIIN 01-521-6584 Monte Carlo Forecast Model versus Actual FY 14 Demand (0% error)

Table 35 shows improved forecast accuracy from 31% (Oct. 2013 model) to 0% (Apr. 2014 model). Notice the reorder point is 192 units.

Six Month Forecast: Comparison of the forecast model vs. actual demand			
		Average	Average
FY_MO	**Actual Product Demand**	**Forecast: 1st model**	**Forecast: 2nd model**
2014-1	13	10.54	15.12
2014-2	16	10.54	15.12
2014-3	16	10.54	15.12
2014-4	14	10.54	15.12
2014-5	14	10.54	15.12
2014-6	18	10.54	15.12
Total	**91**	**63.24**	**90.74**
		Oct. 2013 six month forecast error:	
	0.26	ABS(91-62)/91 = 32%	Apr. 2014 six month forecast error:
Delta forecast #2			error: ABS(91-91)/91= 0%
	All forecasts:		
	FY 2014, six months:	63	91
	FY 2014, twelve months:	127	182
	Lead Time demand, 12 months:	*127*	*182*
	Reorder Point:	145	192

The market for this product is non-static, characterized by shifting conditions.
The Apr-14 forecast used months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.

Table 35. NIIN 01-521-6584 Comparison Second Forecast versus Actual Demand

D. INVENTORY-POLICY FORMULATION: AS CONDITIONS CHANGE, SO MUST INVENTORY POLICY

The results of the Monte Carlo simulation provide guidance for inventory-policy change. Whereas DLA inventory policy for FY14 set the reorder point at 267 units, the April 2014 forecast called for a reorder point of 192 units. That is a difference of 75. At a FY14 price of about $113,265 per unit, the inventory cost reduction would be $8.5 million (with selling price used in lieu of cost), as shown in Table 36.

Evolving Inventory Policy: Narrowing the gap beween the model and the real world			
	Actual DLA QTY	1st forecast	2nd forecast
Effective date:	FY 14	Oct-13	Apr-14
Forecast		127	182
Safety Stock:	4	18	10
Reorder Point:	267	145	192
The market for this product is non-static, characterized by shifting conditions and uncertainty.			
The Apr-14 forecast used 6 months of actual demand data (Oct-13 to Mar-14) to gauge shifting demand.			
FY-14 unit price	Delta	cost savings	cost increase
$113,265	75	$8,494,868	

Table 36. NIIN 01-521-6584 Forecast Model versus Real World Demand

- **Inventory-Management Assumption**

Since this NIIN is a class-A item (as defined in Chapter III), it should be managed with a continuous inventory policy, due to this product's impact on (potential) overall annual revenue.

JMP software training (online) provides the insight, "All [forecast] models are wrong, but some are useful… The illustration below, Figure 154, states that the organization's performance is a function of their learning curve." See how this statement applies to inventory policy formulation in the next section as it discusses the cost reduction benefit of reducing lead time.

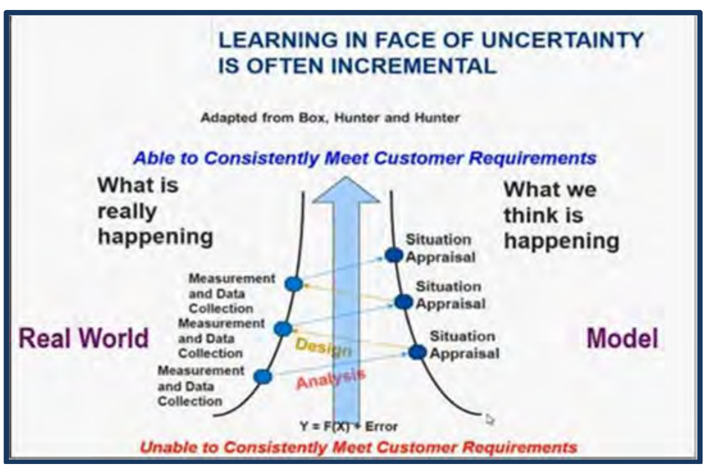


Figure 154. Learning curve, adopted from Exploring Best Practices in Design of Experiments SAS Institute (Webinar 2014.

E. CONDITIONAL-VALUE-AT-RISK ANALYSIS

Figure 155 shows the lead-time demand forecast. The 95% fill rate is shaded blue, and the value of this area under the demand curve is 192 units. Figure 156 shows the range of values of the conditional value at risk (if stock runs out, what is the expected amount?).

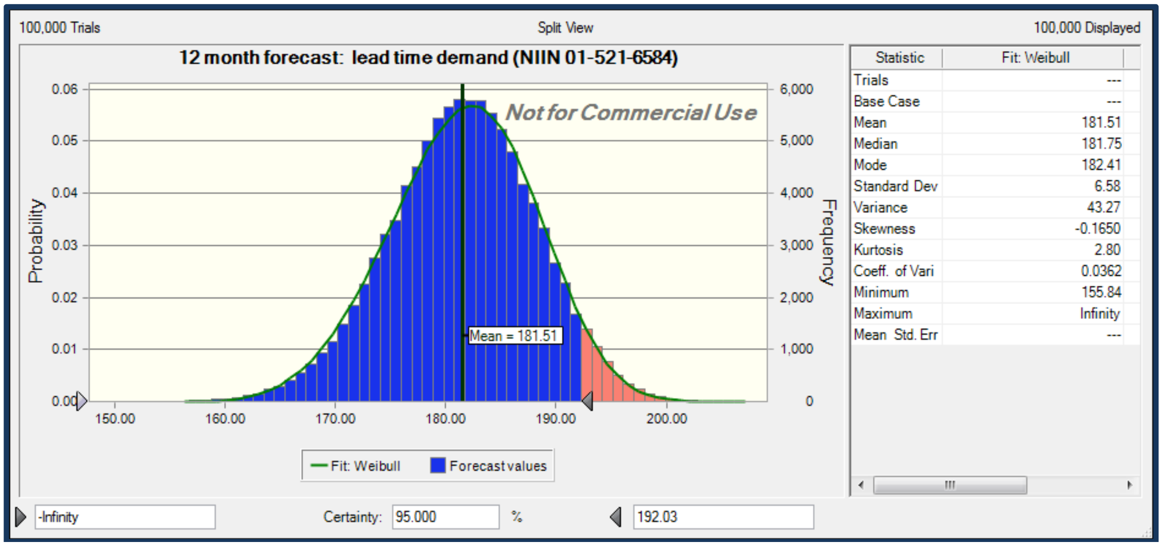


Figure 155. NIIN 01-521-6584 12-Month Lead Time Demand Forecast

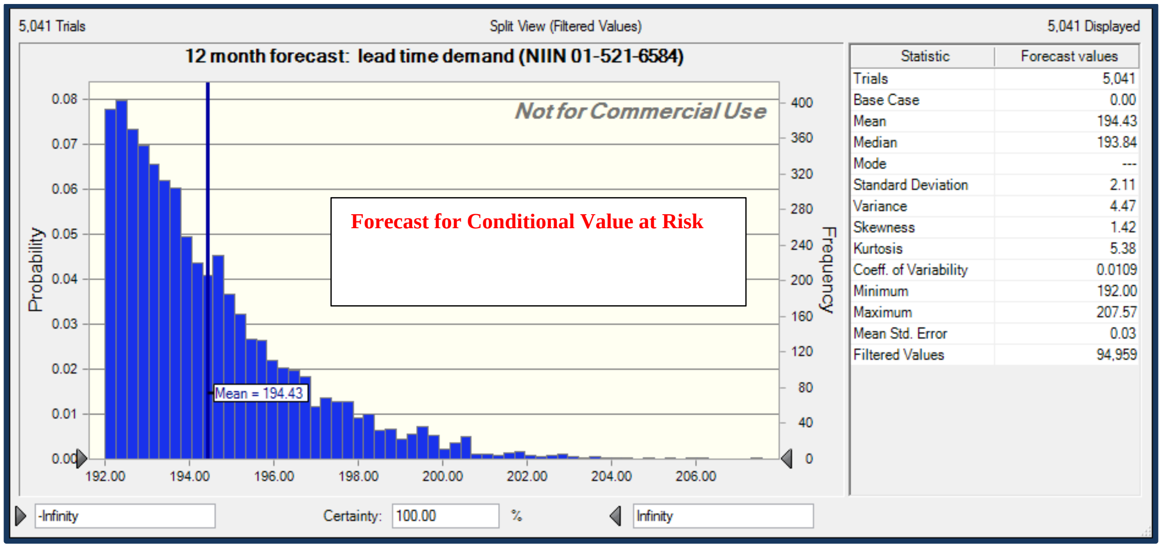


Figure 156. NIIN 01-521-6584 Conditional Value at Risk

The conclusion from the Monte Carlo simulations are summarized in Table 37:

The average lead-time demand forecast (50% probability	**182 units** (lead time = 12 months)
A 95% fill rate quantity equals	**192 units** of inventory
Conditional risk: If demand exceeds stock on hand during the replenishment cycle, the expected shortage is	**3 units** (see forecast right tail distribution: 195 – 192 = 3)
How bad can things get if there is a stock out? The maximum shortage forecasted is	**15 units** (207 – 192 = 15)

Table 37. NIIN 01-521-6584 Lead Time Demand Forecast and Stock out Risk Analysis Summary Table

a. *Improving the Organization's Learning Curve*

The organization should produce demand forecasts and risk analysis for this NIIN on a quarterly basis at least and adjust the inventory policy (reorder point and safety stock levels) as required. This implies integrated planning with the contracting officer and item manager for negotiating the right procurement contract with the supplier(s).

b. *Learning-Curve Potential*

Tables 38 and Figure 157 illustrate that lead time for this NIIN is 353 days (or about twelve months). Reducing the replenishment lead time (admin + procurement) would reduce the exposure period of demand uncertainty and would likely lead to lower safety stock and reorder point, and thus, lower inventory costs.

Lead Time (FY-14)	
procurement lead time days:	340
admin lead time days:	13
total days:	353
months	**12**

Table 38. NIIN 01-521-6584 Admin and Procurement Lead Time

Tabulate

FY	Quarter	FY_MO	FY_MO Series	Calendar Month	niin	itm_name	std_u_price	qty_req Sum	Revenue Sum	alt days 13	plt days 340
2010	1	2010_1	1	10	015216584	PARTS KIT,TURBINE E	$149,310.68	110	$16,424,174.80	11	11
		2010_2	2	11	015216584	PARTS KIT,TURBINE E	$149,310.68	10	$1,493,106.80	5	5
		2010_3	3	12	015216584	PARTS KIT,TURBINE E	$149,310.68	31	$4,628,631.08	14	14
	2	2010_4	4	1	015216584	PARTS KIT,TURBINE E	$149,310.68	37	$5,524,495.16	12	12
		2010_5	5	2	015216584	PARTS KIT,TURBINE E	$149,310.68	27	$4,031,388.36	11	11
		2010_6	6	3	015216584	PARTS KIT,TURBINE E	$149,310.68	17	$2,538,281.56	13	13
	3	2010_7	7	4	015216584	PARTS KIT,TURBINE E	$149,310.68	33	$4,927,252.44	17	17
		2010_8	8	5	015216584	PARTS KIT,TURBINE E	$149,310.68	19	$2,836,902.92	12	12
		2010_9	9	6	015216584	PARTS KIT,TURBINE E	$149,310.68	37	$5,524,495.16	15	15
	4	2010_10	10	7	015216584	PARTS KIT,TURBINE E	$156,176.74	30	$4,685,302.20	11	11
		2010_11	11	8	015216584	PARTS KIT,TURBINE E	$156,176.74	12	$1,874,120.88	10	10
		2010_12	12	9	015216584	PARTS KIT,TURBINE E	$156,176.74	33	$5,153,832.42	13	13
2011	1	2011_1	1	10	015216584	PARTS KIT,TURBINE E	$156,176.74	15	$2,342,651.10	9	9
		2011_2	2	11	015216584	PARTS KIT,TURBINE E	$156,176.74	16	$2,498,827.84	11	11
		2011_3	3	12	015216584	PARTS KIT,TURBINE E	$156,176.74	11	$1,717,944.14	6	6
	2	2011_4	4	1	015216584	PARTS KIT,TURBINE E	$156,176.74	10	$1,561,767.40	6	6
		2011_5	5	2	015216584	PARTS KIT,TURBINE E	$156,176.74	13	$2,030,297.62	8	8
		2011_6	6	3	015216584	PARTS KIT,TURBINE E	$156,176.74	24	$3,748,241.76	11	11
	3	2011_7	7	4	015216584	PARTS KIT,TURBINE E	$156,176.74	19	$2,967,358.06	11	11
		2011_8	8	5	015216584	PARTS KIT,TURBINE E	$156,176.74	24	$3,748,241.76	12	12
		2011_9	9	6	015216584	PARTS KIT,TURBINE E	$156,176.74	17	$2,655,004.58	9	9
	4	2011_10	10	7	015216584	PARTS KIT,TURBINE E	$115,359.93	34	$3,922,237.62	13	13
		2011_11	11	8	015216584	PARTS KIT,TURBINE E	$115,359.93	20	$2,307,198.60	13	13
		2011_12	12	9	015216584	PARTS KIT,TURBINE E	$115,359.93	23	$2,653,278.39	15	15
2012	1	2012_1	1	10	015216584	PARTS KIT,TURBINE E	$115,359.93	24	$2,768,638.32	11	11
		2012_2	2	11	015216584	PARTS KIT,TURBINE E	$115,359.93	22	$2,537,918.46	12	12
		2012_3	3	12	015216584	PARTS KIT,TURBINE E	$115,359.93	40	$4,614,397.20	18	18
	2	2012_4	4	1	015216584	PARTS KIT,TURBINE E	$111,322.33	25	$2,783,058.25	8	8
		2012_5	5	2	015216584	PARTS KIT,TURBINE E	$111,322.33	23	$2,560,413.59	13	13
		2012_6	6	3	015216584	PARTS KIT,TURBINE E	$111,322.33	24	$2,671,735.92	15	15
	3	2012_7	7	4	015216584	PARTS KIT,TURBINE E	$111,322.33	14	$1,558,512.62	11	11
		2012_8	8	5	015216584	PARTS KIT,TURBINE E	$111,322.33	20	$2,226,446.60	11	11
		2012_9	9	6	015216584	PARTS KIT,TURBINE E	$111,322.33	66	$7,347,273.78	7	7
	4	2012_10	10	7	015216584	PARTS KIT,TURBINE E	$106,833.37	16	$1,709,333.92	12	12
		2012_11	11	8	015216584	PARTS KIT,TURBINE E	$106,833.37	13	$1,388,833.81	11	11
		2012_12	12	9	015216584	PARTS KIT,TURBINE E	$106,833.37	20	$2,136,667.40	9	9
2013	1	2013_1	1	10	015216584	PARTS KIT,TURBINE E	$106,833.37	25	$2,670,834.25	14	14
		2013_2	2	11	015216584	PARTS KIT,TURBINE E	$106,833.37	8	$854,666.96	8	8
		2013_3	3	12	015216584	PARTS KIT,TURBINE E	$106,833.37	8	$854,666.96	6	6
	2	2013_4	4	1	015216584	PARTS KIT,TURBINE E	$106,833.37	19	$2,029,834.03	11	11
		2013_5	5	2	015216584	PARTS KIT,TURBINE E	$106,833.37	7	$747,833.59	7	7
		2013_6	6	3	015216584	PARTS KIT,TURBINE E	$106,833.37	12	$1,282,000.44	9	9
	3	2013_7	7	4	015216584	PARTS KIT,TURBINE E	$106,833.37	5	$534,166.85	4	4
		2013_8	8	5	015216584	PARTS KIT,TURBINE E	$106,833.37	14	$1,495,667.18	10	10
		2013_9	9	6	015216584	PARTS KIT,TURBINE E	$106,833.37	15	$1,602,500.55	9	9
	4	2013_10	10	7	015216584	PARTS KIT,TURBINE E	$113,264.91	6	$679,589.46	6	6
		2013_11	11	8	015216584	PARTS KIT,TURBINE E	$113,264.91	12	$1,359,178.92	9	9
		2013_12	12	9	015216584	PARTS KIT,TURBINE E	$113,264.91	13	$1,472,443.83	8	8
2014	1	2014_1	1	10	015216584	PARTS KIT,TURBINE E	$113,264.91	13	$1,472,443.83	8	8
		2014_2	2	11	015216584	PARTS KIT,TURBINE E	$113,264.91	16	$1,812,238.56	9	9
		2014_3	3	12	015216584	PARTS KIT,TURBINE E	$113,264.91	16	$1,812,238.56	9	9
	2	2014_4	4	1	015216584	PARTS KIT,TURBINE E	$113,264.91	14	$1,585,708.74	8	8
		2014_5	5	2	015216584	PARTS KIT,TURBINE E	$113,264.91	14	$1,585,708.74	9	9
		2014_6	6	3	015216584	PARTS KIT,TURBINE E	$113,264.91	18	$2,038,768.38	12	12

Figure 157. NIIN 01-521-6584 Monthly Demand, Admin Lead Time and Production Lead Time

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